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Efficiency achievement in water supply systems—A review

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A B S T R A C T

The worldwide water supply represents a significant portion of the global energy consumption. This energy consumption, related to the collection, treatment and transportation of water, entails a large amount of costs. However, these costs are liable to be minimised with and/or without reduction on energy consumption. The purpose of this paper is to provide a review about measures and methods to achieve water supply systems efficiency. The paper summarises and compares previous investigations in order to provide the state-of-the-art to the reader.

Measures with and without investment in order to reduce costs and energy consumption are presented. The paper also explores the use of hydraulic simulation and optimisation strategies in water supply systems, involving topics such as demand prediction, networks design, pumps operation, real-time operations and renewable energy production. Although the great advances in the area, there are unexplored (or poorly explored) methodologies that can be tested and maybe applied in a large number of water systems. There are also some important issues, mentioned in this paper, which must be considered in order to attend specific requirements of the water industries.

Contents

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1. Introduction

Water and Energy are essential elements for the well-being of the societies. The world energy consumption for water distribution is about 7% of the global energy [3].

Nowadays an increased distance between populations and water sources is observed due to population growth, leading to fast expansions of several water networks. At the same time, the global water consumption has quadrupled in the last 50 years and it is expected that this value would continue to increase [146]. Consequently, the immediate consumers supply without any planned strategy has led to inefficient operated systems, increasing the energy costs for water supply and distribution.

With the actual concerns about sustainable development, the improvement of energy efficiency in Water Supply Systems (WSSs) must be of major importance.

The improvements of energy efficiency in WSSs can pass through simple monitoring operations for leakages control to more complex operations such as the water demand prediction, pump systems optimisation, storage/production reservoir systems optimisation and real-time operations. However, it is important to notice that WSSs should always satisfy the requirements of several consumption sectors, responding to demand in each place, in each time and with appropriate pressures [152]. For this reason, computational modelling becomes an important auxiliary tool for these more complex studies of energy efficiency in WSS [102].

This review paper provides several strategies to improve the energy efficiency of the WSSs (Section 2). The paper also explains the importance of hydraulic simulation and describes some simulation computer programmes available in the market (Section 3). Some of the most applied optimisation methods in the area are investigated, including approaches dealing both with the design and control of the networks and dealing with real-time operations and with the introduction of renewable energy production in the WSSs (Section 4). Real-case applications are also presented as some observations about the importance of the water industries involvement with this kind of studies (Section 5). The discussion section (Section 6) identifies the major key topics on both the reviewed subjects.

2. Energy efficiency in water supply systems

The estimative of water loss in the world is around 30%, meaning that a similar portion of energy is also lost [52]. Multiple factors contribute to these energy losses in the water sector [52]: inefficient pump stations, poor design of the networks, installations and maintenance, old pipes with head loss, bottlenecks in the networks, excessive pressures and inefficient operation strategies.

According to Feldman [52], the main improvements in energy efficiency can be obtained with: (i) pump stations design improvement, (ii) systems design improvement, (iii) variable speed drives (VSD) installation, (iv) efficient operation of pumps and (v) leakages reduction through pressure modulation. The last two topics may present a certain conflict. An efficient pump operation leads to a major use of the pumps during the night (off-peak period) increasing the pressure during that time. On the other hand, the goal of pressure modulation is to minimise pressure over the night in order to reduce leakages. A solution for this conflict can be the isolation of distribution areas (using valves, for example) by means of pressure controlled District Metered Areas (DMA) [52]. This enables the combination of the two methods.

Inefficient pump stations can be caused by inefficient control of the pumps or even by the oversize of the systems. Most existent pump systems are oversized and many of them by more than 20% [74], representing an opportunity for energy efficiency in the WSS.

For the flow control in pump stations, bypass lines, throttling valves or pump speed adjustments can be used. However, the pump speed control is the most efficient of these methods [74]. Variable Speed Drives for centrifugal pumps allow their operation with fixed pressure and variable flow or with fixed flow and variable pressure. This allows the reduction of the number of switches (on/off) by the pumps and the reduction of pipe breaks [52]. Furthermore, according to Gellings [61], these drives have potential to save 10–20% of total pumping energy and Kiselychnyk [84] indicates a possible energy reduction of 27% only with a 10% of pump speed decrease.

The difference between the use of control valves or VSD to control the pumps is that, in the first case, with the closure of the valve, an increase on the head occurs, meaning a large dissipation of energy. In the second case, the reduction of the pump operating speed requires a small operating head, implying less power consumption. Fetyan et al. [53] presented in their work a comparative study between a pump connected to a control valve and a pump using two different kinds of VSD (Scalar and Direct Torque Control) for speed control. In both cases, a reduction in the input power with the speed reduction was observed. However, this reduction was larger with the use of VSD applying the Direct Torque Control.

In the cases with no flow rate variation, the use of VSD is not the best choice for saving energy costs [74]. Alternatively, the pump resize, the reduction of the impeller diameters or even the pump replacement for a new one, can become more efficient interventions [74].

Other measures to enhance the efficiency of the WSS, not referred previously, can be applied, such as (i) the replacement of inefficient equipment, (ii) the leakage management by regular monitoring and maintenance, preventing from both water and energy wastes, (iii) the simple selection of a suitable energy tariff system, or even (iv) the incorporation of renewable energy sources in the systems, reducing fossil fuel dependency.

From all the measures presented, some of them can imply high investment costs, such as equipment replacements or even the incorporation of new equipment. However, some of the measures do not present significant investment costs when compared with the benefits obtained. Moreover, some measures related to management do not need any investment, meaning that, in some cases, the efficiency improvement of the WSS can be obtained without too much effort.

The replacement of some inefficient equipment by high-efficiency pump/motor systems can provide around 10–30% of pumping energy savings [62].

In addition to the energy tariff system modification and the introduction of VSD on pumps, Tsutiya [143] refers some ways to minimise energy costs by reducing the total head of the systems. This can be obtained by reducing the geometric head and the head losses. Head losses reductions can be made by [143]: (i) the correct choice of the pipe diameters in order to obtain an economic velocity of the water (lower velocities reduce head losses) or (ii) by cleaning and/or coating the pipes, reducing the roughness of the pipes. Tsutiya also provides the relation between the Hazen–Williams coefficient and the energy cost variations also listed in Table 1 (note that the roughness coefficient increases with the

Table 1
Values for the annual energy cost increase when the Hazen–Williams coefficient (or C-factor) is reduced from the value 130 [143].

Hazen–Williams coefficient	120	110	100	90	80	70	60	50
Energy cost increase (%)	16	36	62	97	145	214	318	486

reduction of the H–W coefficient). It should be noticed that, when the Hazen–Williams coefficient pass, for example, from 130 to 90, the increase on annual energy costs is 97% [143].

In Tsutiya's work [143] it is also shown that the modification of the tariff system can reduce the monthly cost by 50% and the introduction of VSD on constant speed pumps for flow control bring energy savings of 38%. This method has demonstrated to be better than the control by valves using a by-pass system which presented more than 42% of energy consumption [143].

2.1. Renewable energy sources

Despite the huge contributions of the previously mentioned measures for the improvement of the energy efficiency in WSS, the dependence of these systems on fossil fuel will still being notorious. The best way to make these systems energetically sustainable is through the introduction of renewable energy sources or even extracting the excess of available energy using turbines, for example.

In effect, due to a large number of advantages (environmental and economic), the implementation of renewable energy production in WSS is becoming very common, increasing significantly the number of studies in this subject.

As shown below, there are essentially three distinct kinds of solution for energy production in WSSs, i.e., solutions provided by (1) solar, (2) wind and (3) hydropower generation.

The main obstacle to the implementation of this type of solution for WSSs efficiency is related to the implementation cost. In the particular case of hydropower generation, a more economical alternative can be the use of pumps as turbines (PATs) instead of the installation of a hydroelectric plant which requires costs for both land and new equipment. Among several alternatives, the installation of micro hydroelectric plants stands out. In hydropower systems the use of turbines or pumps operating as turbines (PATs) is usual for the recovery of the excess of energy that is generally lost in the WSSs due to the use of pressure reducing valves (PRVs).

Generally, a turbine can be classified on the basis of principle of operation as: (i) impulse turbine (Pelton, Crossflow and Turgo turbines), changing the direction of flow of a high velocity fluid, or (ii) reaction turbine (Francis, Kaplan/propeller and pumps as turbines), that develops torque by reacting with the fluid pressure or mass. The main problem of turbines is the reduced efficiency, typically between 30% and 60% [22].The turbines selection mainly depends on the pressure head available and on the design flow for the proposed hydropower plant [42].

As the pumps available in the market are more adequate for reduced power and flows and, at the same time, represent lower investment costs, they present advantages for using in micro-hydroelectric plants (5–100 kW) either as pump or as turbine [69]. Furthermore, according to Ramos et al. [122], it is possible to use pumps as turbines with relatively higher efficiency (up to 85%). The main disadvantage is the high PAT dependency on flow rate, which does not allow medium and high variations of flow [22].

Most studies in this field are related to the analysis of the feasibility of the PATs compared to other solutions (for example [89,22,17,56]).

The study of Lopes and Martinez [89] demonstrated that the use of pumps as turbines (PAT) can represent a viable choice especially for installations inferior to 4 kW. A study-case provided feasible options with times of investment return from 4 to 22 months maximum [89].

Caxaria et al. [22] compare the performance of the use of a PAT with the use of a five blade propeller turbine for hydropower generation. The five blade propeller turbine demonstrated to be a very promising solution, with high hydro-mechanical efficiency values. Although the application of a PAT is a viable choice, the five blade turbine has the advantage of noninterference with the normal flow behaviour in the piping.

The work of Fontana et al. [56] provides a study of the use of PATs instead of PRVs for loss reduction and energy production in WSSs. Experimental tests were performed in the city of Naples (Italy). At an initial phase, the authors used a simulation model and genetic algorithms for the optimal location of PRVs for loss reduction. Then, the global or partial replacement of the PRVs by PATs was implemented for hydropower generation. Although the optimal location of PRVs for loss reduction does not maximise the energy production, results have shown that a relatively large energy recovery can be obtained with significant reduction in water losses.

Carravetta et al. [17] proposed a PAT design method, based on a variable operating strategy, for the identification of the PAT performance curve that maximises the produced energy for a certain flow and pressure head distribution pattern. The authors pointed out two main problems related to the design of a small hydropower plant: (i) the lack of a complete series of characteristic curves of industrial PATs and (ii) the need of a strategy for turbine selection.

Wind water pumping, resorting to mechanically coupled wind turbines, has been used since ancient history. However, more recently, turbines have also been electrically coupled [109]. The advantage of the electrical coupling is that the location of the wind turbine is independent of the water pumping location [109]. However, photovoltaic water pumping systems are actually being applied especially in WSS with poor electrical requirements [84].

The work of Muljadi et al. [109] provides an analysis of the dynamics of a wind-turbine water pumping system. The analysis process was illustrated by the simulation results of the system. It was observed that the operating point of the wind turbine was affected by the motor and the water pump characteristics. Non corresponding wind turbine characteristics with water pump characteristics (such as the size) lead to an efficiency degradation and also in a reduction in the operating rotor speed range.

Nayar et al. [110], Muljadi [108], Kolhe et al. [85] and Vongmanee [153] provided works dealing with reasonable efficient photovoltaic (PV) water pumping systems.

The overall optimal operation of a PV pumping water system is only achieved if the transformed mechanical load, converted by the electric motor, matches the maximum power line of the PV generator and if that power line matches the maximum hydraulic output of the pump [110]. Additionally, Kolhe et al. [85] tested the effect of changing the orientation of the PV array and concluded that the output obtained is 20% superior to the compared fixed PV array.

3. Hydraulic simulation

Simulation models are computational representations and/or reproductions of real systems behaviour through functions [155]. Hydraulic simulators are numerical programmes in which it is possible to implement models for water transportation and distribution. These models replicate the nonlinear dynamics of the networks by solving a set of hydraulic equations including conservation of mass and conservation of energy [95]. Therefore, this kind of tool allows the users to get details about all elements of a certain network represented at specific times, providing an important support for management and operational control even for the most complex systems. However, a unique approach for modelling does not exist, not even for the simplest WSS.

The first pipe network digital models appeared with the coming of the digital computers and the FORTRAN programming

language between the sixties and the seventies [155]. Even during the seventies, models became more powerful by running not only steady-state simulations but also extended period simulations and later, in early eighties, the first water quality model was developed [155].

Diverse types of models based on hydraulic equations have been used, such as mass-balance models, regression models, simplified hydraulics and full hydraulic simulation models [90]. More recently, the recourse to Artificial Neural Networks for capturing the knowledge base of a hydraulic simulator and reducing the computational burden, is being proposed and applied (see, for instance, [123]).

A mass-balance model is the simplest method of calculation. This model considers only the flow rate variations in a tank assuming that a pump or some pumps generate the level variations in the tank. However, the pumps head and the minimum pressure at nodes are neglected [90].

Regression models are more accurate than mass-balance models. This kind of model is based on a set of nonlinear equations obtained with the responses of a certain network subjected to distinct demands. The problem of this model is the sensitivity to the data used for the construction of the model, meaning that some changes in the network can produce invalid results [90].

The method of simplified hydraulics incorporates the effect of connected components that compose the network into a single equation. In particular cases, some linear equations are enough to represent the system hydraulics [90]. However, it becomes different in complex real cases.

Models based on a full hydraulic simulation are robust in terms of system modifications and demand variations [90]. These kinds of models solve the equations of both mass and energy conservation and these are the most used currently.

Over recent years, there has been a significant increase in the number of software applications in this field [132]. The appearance of such hydraulic simulators has developed from *trial and error* to more advanced optimisation methodologies [95] in order to improve the efficiency of the WSS.

3.1. GIS integration

Nowadays, the integration of Geographic Information Systems (GIS) with hydraulic simulators is quite common [162,96,122, 45,76].

A GIS is a system that allows capturing, managing, analysing and displaying information geographically referenced [63]. This kind of system is useful for the management of projects involving large volume of data and for the application of some analytical tools. In hydraulic simulation works, importing the model results into GIS provides high quality result display and additional analysis possibilities [97]. Therefore, this tool can be used as a source for modelling data and for decision support [156], aiding with time and cost savings and contributing to the efficiency improvement.

The typical benefits of combining GIS with a hydraulic simulator are [96]: (i) automatic calculation of the pipes length, (ii) a map display with more details, scale-dependent, more flexible, etc., (iii) advanced editing capabilities, (iv) interpolation of the elevation data and (v) demand calculation.

Contrary to some hydraulic simulators, in GIS, pumps and valves are usually represented by points (or nodes) and not by links, which requires a special treatment [97].

3.2. Types of hydraulic simulators

Currently, several software programmes for the hydraulic simulation incorporate a number of other additional tools including SCADA systems and optimisation and calibration modules. Some of these programmes are available in free versions and most of them have no limitation in the networks size.

EPANET 2.0 [126], for example, is a free open source software, developed by the EPA (U.S. Environmental Protection Agency), that performs extended period simulation of hydraulic and quality behaviour within pressurised pipe networks [49]. This simulator is characterised by a robust model with a large community of users in the world [151], offering an optional user interface and no limitation on the network elements number. It allows the use of metric or US units and supports the commonly used head loss calculation: Darcy–Weisbach, Hazen–Williams and Chezy–Manning.

Several applications using EPANET have been developed, such as: (1) EPANET Z displays online maps/imagery as a background [164]; (2) EpaSens performs sensitivity analyses to the network parameters [165]; (3) epa2GIS exports the network map and outputs from EPANET to a Geographic Information System environment [163]; (4) GHydraulics also integrates EPANET with GIS and calculates economic diameters for specific flow rates [96]; (5) GISRed integrates EPANET with a ArcView GIS [124]; (6) EISM is another add-on that allows to import/export data for MapGuide through INP format [73]; (7) DC Water Design Extension is another ArcView solution [45]; (8) HydrauliCAD, an AutoCAD hydraulic analysis water modelling programme that uses EPANET calculations [75]; etc. Due to all these facilities and the fact of being in the public domain, EPANET is the mostly used hydraulic simulator in academic field. However, several commercial programmes are already applied in industry. A number of these existing commercial computer programmes employ EPANET as a basis for the hydraulic modelling and separate modules for the networks optimisation. This is, for example, the case of:

- *AQUIS* [1], a water distribution modelling and management programme that includes not only hydraulic simulation but also pipe design and control optimisation and integrates a calibration module, SCADA and GIS systems;
- *Aquadapt* [39], that allows obtaining the e optimal operations (with minimum energy) of an entire network making use of the SCADA facilities;
- *ENCOMS/CAPCOMS* [70], that incorporates calibration, pipe design and control optimisation modules with a SCADA system;
- *Helix delta-Q* [72], that only allows the design optimisation of the networks;
- *H_2ONET/H_2OMAP* [79] provides calibration, pipe design and control optimisation using GIS and SCADA facilities;
- *Mike Net* [40], that incorporates optimisation and calibration modules, uses a GA and includes SCADA and GIS facilities;
- *optiDesigner* [115], that also uses GA to find the least-cost design of the networks;
- *Optimizer WDS* [114], that allows design and operational optimisation in real-time and the application of distinct optimisation algorithms for distinct cases, such as Evolutionary Algorithms, Genetic Algorithms, Non-Linear Programming and also Artificial Neural Networks when a reduced computer runtime is needed;
- *SynerGEE Water* [65], that includes GIS and SCADA systems and provides a module for pipe design optimisation;
- *STANET* [137], like the SynerGEE Water, includes GIS and SCADA facilities and a pipe design optimisation module;
- *Wadiso* [66], also for the optimal design of the networks, integrating GIS and SCADA systems;
- *WaterCAD/WaterGEMS* [12], another robust hydraulic simulator on the basis of EPANET that incorporates GIS facilities (WaterGEMS) and both calibration, optimisation (design and control) and SCADA modules.

Other kind of commercial hydraulic simulators not based on EPANET are also available in the market, such as:

- *Aquadapt* [39], that includes management optimisation of the networks making use of GIS and SCADA facilities;
- *AquaNet* [77], a simple pipe system modelling software;
- *Cross* [125], another computer programme that only performs pipe systems simulation;
- *Eraclito* [121], a hydraulic simulator with similar characteristics to the Aquadapt;
- *HYDROFLO* [141] also for hydraulic simulation; the developers of this simulator also offer **PumpBase 2.0**, an advanced pump selection software;
- *MISER* [145], similarly to Aquadapt and Eraclito, this is a hydraulic simulator that also allows the optimisation of the networks management, incorporating GIS and SCADA systems;
- *Pipe2012* [86] is a more advanced computer programme for water network management, grouping modules such as calibration and optimisation (design and control), using GIS and SCADA facilities.

Although EPANET 2.0 is actually the most widely used hydraulic simulator, other public domain computer programmes exist, however, with some limitations. It is the case of:

- *Branch/Loop*, where Branch calculates the least-cost design of branched water distribution networks using linear programming and Loop simulates the hydraulic behaviour of looped networks. The main disadvantage of the Branch/Loop software is its limitation on the size of the networks [132].
- *NeatWork* [111], uniquely determines the optimal design of water gravity networks for rural areas.

4. Optimisation in water supply systems

The development of water supply systems without the use of optimisation provides non-optimal structures, based essentially on the immediate response to the growing water demand of population and industry [84]. These non-optimal structures are translated into non-efficient systems in terms of design and operation.

Although reproducing the hydraulic behaviour of the systems, a hydraulic simulator does not allow the determination of the optimal structures or the optimal operational conditions of the systems. For these reasons, recourse to the optimisation tools is crucial.

Optimisation problems can be solved using conventional *trial and error* methods or more effective optimisation methods. However, in water supply systems, the optimisation process by *trial and error* methods can present difficulties due to the complexity of these systems such as multiple pumps, valves and reservoirs, head losses, large variations in pressure values, several demand loads, etc. For this reason, innovative nonlinear optimisation algorithms are becoming more widely explored in optimisation processes of the water supply systems.

A general optimisation problem is defined as the minimisation (or maximisation) of a function f subject to equality and/or inequality constraints and can be expressed as [29]:

$$\begin{array}{lll} \text{min (or max)} & f(\mathbf{X}) & \\ \quad\text{subject to} & g_m(\mathbf{X}) \le 0, & m = 1, \ldots, M, \\ & h_l(\mathbf{X}) = 0, & l = 1, \ldots, L \end{array} \tag{1}$$

where $\mathbf{X} = (x_1, \ldots, x_n)$ is a vector of the decision variables (continuous or discrete) with dimension n; M and L are, respectively, the number of inequality and equality constraints that must be satisfied during the optimisation of the objective function f. These constraints are usually related to the system hydraulic requirements such as equations of mass and energy conservation, design and/or operational parameters bounds, nodal pressure head bounds and other parameters dependent on both pressure head and design/operational parameters.

Actually, there is no "perfect" algorithm to solve all the optimisation problems. For the WSSs case, this can be also observed. During the past decades, a large variety of nonlinear optimisation techniques have been applied for the design and operational optimisation of the water networks.

Nonlinear optimisation algorithms can be distinguished according to two general classifications [26]: (i) classical algorithms, based essentially on the computation of the objective function gradient and/or function evaluations and (ii) heuristic algorithms, consisting essentially on exploratory search and generally based on a phenomena that occur in nature or even based on artificial intelligence.

The classic algorithms applied in WSS optimisation comprise: Linear Programming (LP), Nonlinear Programming (NLP), Integer Nonlinear Programming and Dynamic Programming. These kinds of algorithms enable finding the exact position of an optimal solution. However, they usually converge to local optimal solutions which could not be the global optimum. In addition, the need of derivative evaluations can, in some cases, complicate the optimisation process.

From the group of heuristic algorithms, it is usual to find works mostly applying the Genetic Algorithms (GA) and Evolutionary Algorithms (EA). However, other techniques have also been investigated, such as Particle Swarm Optimisation (PSO), Tabu Search (TS), Ant Colony Optimisation (ACO), Simulated Annealing (SA), Shuffled Complex Evolution (SCE) and Harmony Search (HS). These techniques provide the advantages of not requiring derivatives calculations and not relying on the initial decision variables. Due to the exploratory nature of the heuristic algorithms, the probability of finding global optimal solutions using these advanced techniques is higher [26]. On the other hand, the main disadvantage of these methods is related to the higher computational effort [26].

The concept of hybrid algorithms combining global optimisation with local search techniques in order to increase the convergence is also largely observed in the literature for the optimisation of WSSs.

Some researchers frequently explore the optimisation problems through a multi-objective perspective, dealing with the minimisation (or maximisation) of a number of functions or even dealing with conflicting objectives, which imply the minimisation of some functions and, at the same time, the maximisation of other functions.

The goal of a multi-objective problem (MOP) is then to optimise (minimise and/or maximise) a number of objective functions simultaneously [29]. The general formulation of a MOP can be stated as [29]:

$$\begin{array}{lll} \text{min (or max)} & F(\mathbf{X}) = (f_1(\mathbf{X}), \ldots, f_k(\mathbf{X})) & \\ \quad\text{subject to} & g_m(\mathbf{X}) \le 0, & m = 1, \ldots, M, \\ & h_l(\mathbf{X}) = 0, & l = 1, \ldots, L, \end{array} \tag{2}$$

where k is the number of objective functions.

Cheung et al. [25] pointed out five objectives that constitute a complex MOP for a WSS: (1) hydraulic capacity, (2) physical integrity, (3) flexibility, (4) water quality and (5) economy. However, in the literature, most MOPs applied to WSS optimisation are represented by two general objectives: costs minimisation and hydraulic benefits maximisation.

Multi-objective optimisation methods have the advantage of providing a set of optimal solutions, called Pareto optimum,

instead of a unique optimal solution [29]. This allows the system operator to analyse the set of Pareto optimal solutions and choose one solution considering additional criteria.

Evolutionary algorithms are usually the most used for solving MOPs. While the evolutionary methods deal with a set of solutions during the search procedure, allowing to obtain a set of Pareto optimal solutions in a single run, the classic methods only lead to a single solution and cannot guarantee the generation of different points on the Pareto front (non-dominated Pareto solutions) [25].

With respect to the constraints to which the objective function should obey in order to not reproduce unfeasible solutions, Michalewicz [105] and then Coello [28] provided reviews about the state-of-the-art constraint-handling techniques applied on evolutionary computation. Michalewicz [105] classified the techniques possible to be used in nature-inspired algorithms as: (1) penalty functions, which can be static (function of the degree of violation of constraints) or dynamic (function of both the degree of violation and the number of iterations); (2) rejection of unfeasible individuals; (3) specialised operators; (4) the assumption of the superiority of feasible over unfeasible solutions; (5) behavioural memory; (6) repair algorithms; (7) multi-objective optimisation; (8) co-evolutionary models or even (9) cultural algorithms. Coello [28] followed a similar classification and also pointed out the specific advantages and disadvantages of each type of constraint-handling technique.

Recently, Mallipeddi and Suganthan [100] also provided a work dealing with constraints. Motivated by the fact that different constraint-handling techniques can be effective in distinct stages of the optimisation, the authors proposed and tested the behaviour of an ensemble of constraint-handling techniques (ECHT) to solve constrained real-parameter optimisation problems. The ensemble is composed of four distinct techniques. Results showed that the ECHT outperformed each of the constraint-handling method that constitute the ensemble [100].

4.1. Design optimisation

Design optimisation problems in WSS are based on searching the system characteristics which minimise the total system cost without affecting the proper operation of the hydraulic system and the consumers supply. This means that the system must be economic and reliable. However, increase in reliability can imply higher costs [140].

According to Gellings [62], pipeline optimisation can save up to 5–20% of the pumping energy.

The main obstacles in designing highly-efficient systems are [84,5]: their complexity, spatial distribution, changeable structure, time-varying parameters, availability of discrete and continuous control actions and large range of possible combinations of pipe materials.

Typically, in this kind of optimisation problem, the objective function is expressed as a function of costs that can be associated to distinct water supply components such as sources/pumping plants, pipelines, reservoirs and residential connexion or even costs associated to energy consumption and establishment costs related to the land, to the operational staff or other facilities [140].

The total costs can also be classified into two main types [140]: (1) capital costs, associated to the initial investment and (2) recurring costs, required to keep the operational conditions. Thus, the general WSS design problem can be formulated as the minimisation of the total costs represented by the sum of these two main types of cost (capital and operational), subject to the conservation laws of mass and energy, to the water demand constraints and to the nodal head requirements [5]. Nevertheless, other constraints can also be considered in order to improve the model, such as constraints related to the layout, multiple loadings, uncertainty due to lack of information, operations, water quality, reliability and rehabilitation [5].

Swamee and Sharma [140] proposed single expressions, essentially dependent on the materials and dimensions of the elements, for the contribution of each water supply component (pumps, pipes, high-pressure pipes, service reservoirs, surface reservoirs and service connexions) for the total capital costs.

The annual recurring cost of energy consumed in maintaining the flow (or pumping energy cost) can be obtained by multiplying the average pump power by the electricity cost and the total number of hours in a year. As referred by Amit and Ramachandran [5], in order to develop a good model for the design optimisation of WSS, some aspects must be included: (a) pipe layout and sizes, (b) location and capacity of tanks, (c) location, types, capacity and operating schedule of pumps and (d) location, types and settings of valves. Additionally, multiple loading demands, reliability, uncertainty and water quality should also be considered in order to satisfy the requirements of real WSS.

The design optimisation review paper published by Amit and Ramachandran [5], based on the networks configurations, provides distinct models developed either for branched or for looped networks.

Ostfeld and Tubaltzev [117] classified the design optimisation models developed and published, since the seventies, into six different types, according to the optimisation methodology applied: (1) Decomposition, where the problem is solved using linear programming for a number of fixed flows and the alteration of the flows is made by gradient-based methods; (2) Simulation and Nonlinear Programming, based on a connexion between a network simulator and a nonlinear algorithm; (3) Nonlinear Programming, models based only on the use of a nonlinear programming formulation; (4) Evolutionary/Meta-heuristic Methods, where, most of times, the Genetic Algorithms are used, but also the Simulated Annealing, the Ant Colony Optimisation, etc.; (5) Multi-objective Evolutionary Methods, which evaluate the least-cost design in parallel with other related objectives; and (6) Other methods, like Dynamic Programming and Integer Programming.

In most works dealing with optimisation design of WSS, some benchmark networks have been constantly used for the comparison between distinct developed methodologies: (a) the two-loop network, a gravity network with a single source, firstly introduced by Alperovits and Shamir [4], (b) the two-reservoir network, introduced by Gessler ([64] *apud* [135]), (c) the New York City Tunnels (Schaake et al., [131] *apud* [37]), (d) the Hanoi network in Vietnam (Fujiwara and Khang [58] *apud* [88]) and (e) the Anytown, USA, introduced by Walski et al. [154]. Both networks are represented in Fig. 1.

The objective of the simple two-loop problem (see Fig. 1a) is to modify the pipe diameters in order to find the least cost.

The problem of the two-reservoir network (Fig. 1b) consists in the diameter selection of five new pipes and the clean, duplication or left alone of the three existing pipes. The system also includes three demand patterns to satisfy.

The New York City Tunnels problem (Fig. 1c) consists essentially of a single source in Hill View and two main city tunnels. The objective of this problem is to determine the need of laying a new pipe parallel to the existing ones and also to determine their diameters. A unique demand case is considered.

The Hanoi network (Fig. 1d) contains three loops and also ramifications. The objective of this problem is to find the least-cost diameters for all pipes while respecting the minimum value for the head pressure at each node.

Finally, the Anytown problem (Fig. 1e) is the more realistic system, providing some typical features and problems such as pump and tank sizing ,location and also pipe sizing. However, the problem does not consider neither the multiple pressure zones nor the multiple demand loads.

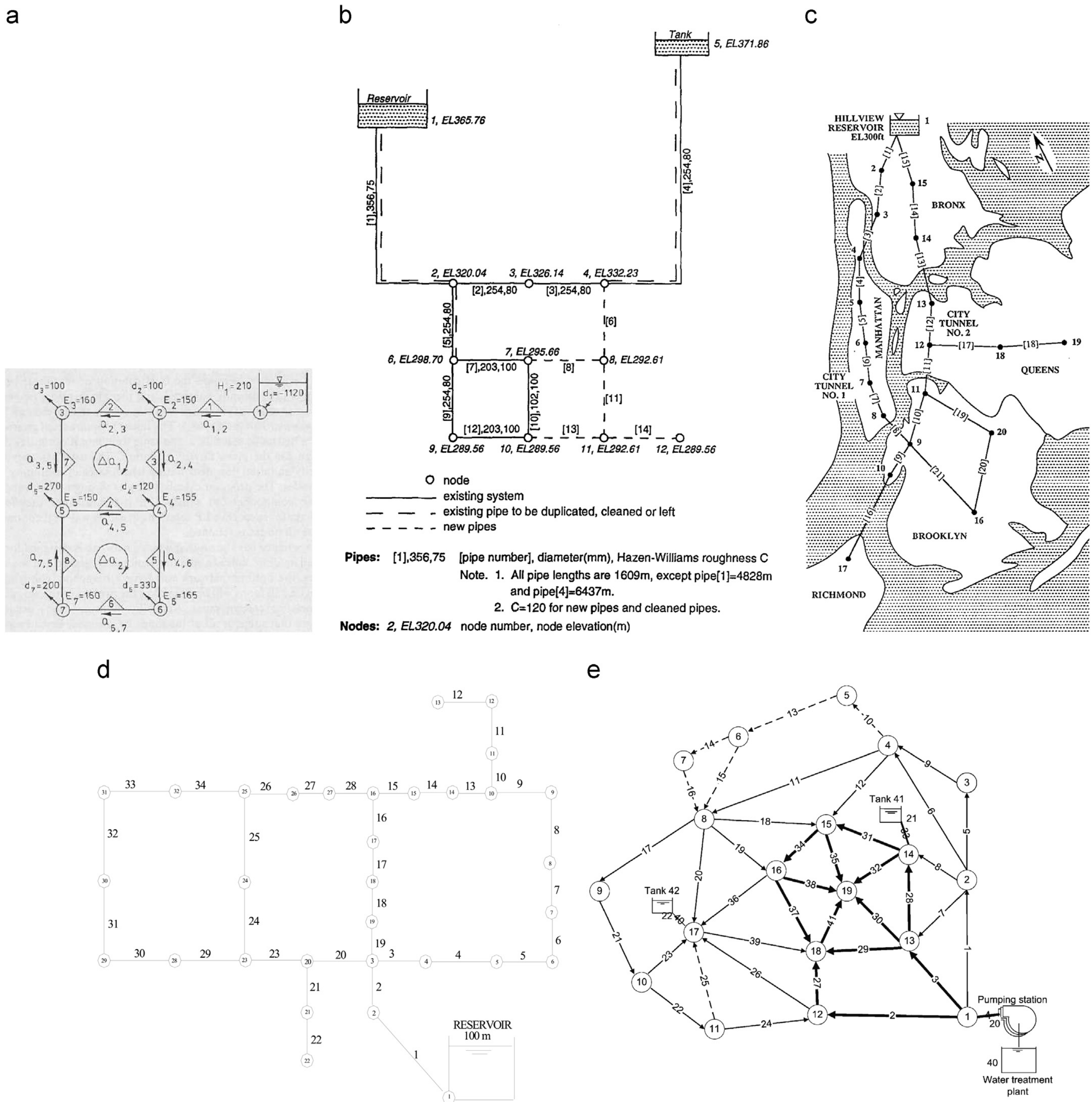

Fig. 1. Representation of the most tested benchmark water supply networks for design optimisation: (a) two-loop network [4], (b) two-reservoir network (Gessler, 1985 *apud* [135]), (c) New York City Tunnels (Schaake et al., 1969 *apud* [37]), (d) Hanoi (Fujiwara and Khang, 1990 *apud* [88]) and (e) Anytown ([154] *apud* [51]).

Alperovits et al. [4], Kessler and Shamir [83] and Eiger et al. [48] are examples of works where decomposition methodology was applied.

First proposed by Alperovits et al. [4], the decomposition approach consists of a hierarchical two-stage decomposition of the optimisation problem. In the first stage, the flows are provided by the user and the local optimal conditions of the network (pipe segments and nodal pressure heads) are obtained solving a linear problem. For the second stage, the authors propose the calculation of the gradient of the total cost with respect to the changes in flow in order to find the flows which provide the minimum cost. The main advantages of this linear programming gradient model are that (a) it deals with dimensions, locations, capacities and/or operation of the several elements of the networks, (b) deals with multiple loadings and, (c) for each loading, it provides hydraulically feasible designs [4]. On the other hand, some weaknesses can also be pointed, such as (i) the need for selection of the initial flow distribution of the networks, (ii) the objective function do not reflect aspects such as performance and reliability of the networks and (iii) the flows in reservoirs are considered fixed, meaning that their capacity is not considered [4].

Kessler and Shamir [83] reformulated the previous model applying matrix notations by means of graph theory formulation. This change in the formulation has brought independency to the

gradient of the objective function of the sets of loops and paths selected in the first stage. The search in the second stage was improved by using the projected gradient method.

The works following the approach of Alperovits and Shamir using gradient calculations ignored the fact that it is not always possible to calculate the gradient. An example to overcome this problem can be seen in the work of Eiger et al. [48] that presented a strategy applying a global search in the decomposition method considering the gap between the solution and the global optimum. The authors applied a Branch and Bound algorithm that reaches the solution through the combination of a primal process to improve local solutions with a dual process to compress the global bound. It was observed that the algorithm stops in a defined gap between the best value obtained and the lower global bound. When compared with previous results obtained with a decomposition method, for the same examples of networks (including the two-loop and the Hanoi networks), this new approach using global search seems to have greater potential. However, also in this model, there were no considerations to the systems reliability and water quality constraints.

A reliable WSS is a system that satisfies nodal demands and pressure heads for a number of possible pipe failures [139]. To determine the reliability of a WSS, the Minimum Cut-Set Method was considered by Tung [144] as the most efficient method when compared with other five techniques: (1) Conditional Probability Approach, (2) Tie Set Analysis, (3) Connexion Matrix Method, (4) Event Tree Technique and (5) Fault Tree Analysis. A minimum cut-set is a set of components of the WSS that makes the system fail only when failures occur in the entire set [139]. The main failures in water systems occur essentially due to corrosion, excessive load or temperature [104].

Su et al. [139] introduced continuity and reliability constraints in their model. The developed model is composed of three linkable modules: (1) a steady-state simulation module which incorporates a KYPIPE simulator (referred in Sections 4.2), (2) a reliability module and (3) an optimisation module based on a generalised reduced-gradient method [139].

In the work presented by Su et al. [139], the reliability of a system is expressed in terms of failure probability of the minimum cut-set that can be determined by the Poisson probability distribution. The disadvantages pointed in the model developed by Su et al. [138] are: (1) the resulting pipe diameters that could not be commercially available, (2) the considerable computational effort required for large looped networks, (3) no multiple loading conditions were considered and (4) the need to incorporate several components (pumps, tanks, valves, etc.), that difficult the problem when the reliability for each component must be defined.

Mays [104] provides in detail definitions of reliability for each component of a WSS.

Over the years, Genetic Algorithms (GAs) have demonstrated to be effective at solving water design optimisation problems, however the search for optimal or near optimal solutions become more difficult with the increase of the problems dimension.

Simpson et al. [135] provided a comparative study between GAs and other techniques for pipe optimisation: (1) Complete Enumeration and (2) Generalised Reduced Gradient (through a nonlinear package based on this algorithm). Both the methods were used to optimise the two-reservoir network and the results were compared with the firstly obtained by Gessler [Gessler, 1985 *apud* [135]]. Multiple loading conditions were considered and a steady-state solver was used for the hydraulic analysis of the network. Using the Complete Enumeration, the same solution obtained previously by Gessler and also an even better solution were found [135]. This technique demonstrated to be effective for networks with few pipes [135]. With respect to the nonlinear method applied, it looked to work well for small extensions of the networks [135]. The GA was particularly effective in finding global optimal or near-optimal solutions with the advantage of providing alternative solutions which sometimes could be preferred [135]. In this case, binary strings were used for the codification of the available pipe sizes.

Dandy et al. [37] presented an improved GA that led to better results than the simple GA. The improvements include [37]: (a) use of Grey codes, (b) use of an exponent fitness scaling, where the value of the exponent is adapted which increases in generations without stagnation, and (c) application of an adjacent (or creeping) mutation operator, based on the replacement of a complete decision variable substring by an adjacent possibility from the list of decision variables. The improved GA was applied to the New York City water supply tunnels. The obtained results were compared with solutions using other techniques (Linear Programming, decomposition techniques and heuristic methods) and improvements were achieved with feasible solutions [37].

After discovering, in previous works, inconsistencies in network performance predictions caused by distinct interpretations of the Hazen–Williams equation, Savic and Walters [129] tested the application of different numerical conversion constants ω for the head loss equation that can be defined by [155]:

$$h_L = \frac{\omega L}{C^z D^{4.87}} Q^z, \tag{3}$$

where L and D are, respectively, the length and the diameter of pipe, C represents the Hazen–Williams coefficient, Q is the pipe flow rate and $z=1.852$ (SI units). The use of distinct values for this conversion factor was also observed in later works (see, for instance, results presented on Appendix A4).

The developed computer model GANET (a GA in cooperation with EPANET) was used and the values tested for the constants were $\omega=10.9031$ and $\omega=10.5088$. The benchmark networks tested were (1) the two-loop, (2) the Hanoi and (3) the New York City Tunnels, and distinct results were obtained for each constant used. It should be pointed out that their results were better than some obtained by other researchers, demonstrating the potential of GANET for the design optimisation. The improvements applied to GA in the GANET include [129]: (a) Grey codes for the variables representation instead of the common binary codes and (b) penalty terms added to the fitness function in the case of pressure-infeasible solutions (the penalty is a function of the distance from the feasibility).

Djebedjian et al. [41] tested the two-loop network design optimisation using the Sequential Unconstrained Minimisation Technique (SUMT) proposed by Fiacco and McCormick ([54] *apud* [41]) however firstly introduced by Carroll ([19] *apud* [41]). Results were identical to that obtained previously by Savic and Walters [129].

Wu and Simpson [160] investigated the use of Genetic-Evolutionary optimisation algorithms in water networks. The authors developed an algorithm, called messy GA, which is characterised by a modified GA according to the following issues [160]: (a) strings with variable length, (b) search technique using building blocks, where genes in a string are randomly deleted in order to find building blocks containing only good genes, (c) threshold selection in order to ensure that strings only compete when containing some genes from the same gene locus, and (d) cut and splice operators, used for a messy genetic reproduction. The messy GA was integrated with the hydraulic simulator EPANET (referred in Section 4.2) for solving the systems hydraulic equations in each iteration. Also constraints for pressure, pipe flow, pump capacity, valve settings and tank flow were considered. The model was applied in the two-reservoir network, also tested by Gessler (Gessler, 1985 *apud* [135]) and Simpson et al. [135], and in the New York City Tunnels. The performance of the model in a real WSS in Morocco was also investigated. Results showed that in

the two benchmark problems, the messy GA found good solutions when compared with the previous studies, always with a significantly reduced computational effort [160]. In the real case of Morocco, the messy GA demonstrated a faster convergence to better solutions when compared with a simple GA, both starting with similar initial design solutions [160].

Later, Wu and Simpson improved their messy GA and introduced the Self-Adaptive Boundary fast messy GA that was tested in the New York City Tunnels problem [161]. The algorithm was able to find the same solution as the obtained using the messy GA but with a reduced number of the objective function evaluations [161].

Abebe and Solomatine [2] integrated the simulator EPANET with a global optimisation tool (GLOBE) composed of various search algorithms including: controlled random search (two distinct versions, CRS2 and CRS4), genetic algorithm (GA) and adaptive clustering covering with local search (ACCOL). The authors handled the constraints grouping them into hydrodynamic, minimum head and commercial constraints. The hydraulic simulator automatically deals with hydrodynamic constraints, however, for the minimum nodal head violations, penalty functions are applied. The commercial constraints are directly related to the available pipe sizes (discrete space search).

The programme developed by Abebe and Solomatine [2] was tested with the two-loop and the Hanoi networks. The results demonstrated, as in previous works, the good performance of the GA dealing with this kind of problem. The ACCOL also demonstrated a good performance in both tested networks of the literature.

A comparison between Ant Colony Optimisation (ACO) and Genetic Algorithms applied to the design optimisation of WSS is provided by Maier et al. [99]. In their model, ACO is linked with the hydraulic solver Wadiso (see Section 4.2). The ACO has the advantage of considering more available pipe sizes (a larger search space) due to the binary strings dimension. The algorithm also has an improved search into regions where good solutions have been found before.

The ACO demonstrated a similar performance to the GA of Simpson et al. [135] in the two-reservoir network and a slightly better performance in the New York City Tunnels, obtaining a feasible global solution [99].

Zecchin et al. [162] provide a comparison between five ACO algorithms applied to the two-reservoir problem, to the New York City Tunnels, to the Hanoi problem and to a doubled New York Tunnels problem (2NYTP), consisting of two New York Tunnels networks connected via a single reservoir. The compared algorithms were: (1) Ant System (AS), the original and simplest ACO [[44] *apud* [162]], (2) Ant Colony System (ACS), that adds probabilistic rules to determine whether an ant is to act and also present a “local” updating of the pheromone, encouraging the exploration of alternative edges ([43] *apud* [162]), (3) Elitist Ant System (AS_{elite}), consisting in the use “elitist ants” in order to maintain the global-best paths after each iteration [[44] *apud* [162]], (4) Elitist-Rank Ant System (AS_{rank}), that includes a rank-based updating at each iteration ([15] *apud* [162]), and (5) Max–Min Ant System (MMAS), that was developed to solve premature convergence by encouraging local search around the best solution found in each iteration ([138] *apud* [162]). The performance of these five ACO algorithms was also compared to other techniques previously applied in the same networks, including some of them presented in this paper.

In the case of the New York City Tunnels and the Hanoi network, previous studies have reached lower values for the cost function [129,159]; however Zecchin et al. [162] stated that those solutions have revealed to be infeasible when analysed by EPANET 2.0. This fact is a demonstration of the extreme importance of choosing a good hydraulic simulator in order to provide correct information respecting to the feasibility of the solutions.

AS_{rank} produced a better average performance for the NYCT and MMAS demonstrated to be the best performing algorithm for the Hanoi network [162].

For the two-reservoir network, although both ACO algorithms reached the global optimum, the AS_{elite} and AS_{rank} demonstrated higher efficiency [162] even when compared with the best value obtained from other studies [99]. The MMAS is referred to present the best performance for the 2NYTP [162].

Globally, the AS_{rank} and the MMAS presented consistently good performances in both the case studies standing out from the others algorithms [162].

In the study of Zecchin et al. [162] it is clearly observed that a certain optimisation algorithm can provide the best solution for a certain network but not so good for others. This is one of the reasons why the combination of distinct algorithms is advantageous.

Ostfeld and Tubaltzev [117] applied an ACO algorithm linked with EPANET for the Anytown least-cost design and operation. The design variables considered in this work were the pipe diameters, the pumping maximum power and the tanks storage. Domain pressures at the consumer nodes, maximum amount of water allowed from the source and tanks storage closure were treated as constraints. The Anytown network was slightly modified by an additional source connected to node 9 and a tank to node 4 (see Fig. 1(e)). The objective function, in this optimisation problem, includes not only pipe construction cost but also operational and construction cost of pumps and tanks. The proposed algorithm scheme is based on the work by Dorigo et al. ([44] apud [115]) and Maier et al. [99] with some modifications. The only restrictions pointed out by the authors for their methodology are: the fact of the pumps efficiency being considered constant, reliability improvements and fire flow requirements not considered and the use of linear penalty functions instead of more sophisticated constrained handling mechanisms. The first problem respecting the constant pump efficiency consideration can be easily overcome since EPANET allows the introduction of an efficiency curve for each pump. Respecting the use of a different constraint handling mechanism, the application of quadratic penalty functions or the Augmented Lagrange multipliers technique may be interesting alternatives since these methods have presented great performances in several engineering problems (see, for instance, [7]).

Liong and Atiquzzaman [88] proposed an algorithm called Shuffled Complex Evolution (SCE) for the design optimisation of a WSS. The SCE, developed by Duan et al. [[47] *apud* [88]], consists of synthesis of four successful concepts in global optimisation: (1) combination of probabilistic and deterministic concepts, (2) clustering, (3) systematic evolution of a complex of points covering the search space in direction to a global improvement and (4) competitive evolution. The global improvements are made through the modification of points from each complex using the Nelder and Mead Simplex method [112]. Pressure head constraints were treated with penalty cost functions based on the degree of pressure head violation.

The methodology proposed by Liong and Atiquzzaman [88], coupling the SCE algorithm with EPANET, was tested in the two-loop and Hanoi networks. For the two-loop network, the results were the same as the ones obtained by other techniques applied before (GA, GLOBE, Simulated Annealing and Shuffled Frog Leaping Algorithm). However, these results were obtained with a considerable lower number of function evaluations. In the Hanoi case, the optimum obtained by the SCE algorithm was also reached in a considerable reduced computational effort.

Cunha and Ribeiro [34] proposed the use of Tabu Search algorithms for the optimal design of a WSS. Two configurations of this kind of algorithm were tested in five examples of network including the two-loop, the New York City Tunnels and the Hanoi.

The proposed algorithms were able to obtain identical solutions to the best ones found in previous works for the two-loop and the Hanoi networks. In the case of the New York City Tunnels, the Tabu Search technique was able to find a solution with the same cost obtained by Savic and Walters [129]. For the remaining two cases (one containing a single tank, another with two tanks and both of them with multiple loops), improvements were achieved, demonstrating that the number of benchmark networks being tested in the literature is not enough to conclude about which meta-heuristic algorithm is the most appropriate for this kind of problem.

Geem [59] developed an algorithm called Harmony Search (HS) which was connected to EPANET for the optimisation of the following networks: (i) two-loop, (ii) Hanoi, (iii) New York City Tunnels and (ii) two distinct networks from South Korea. Cost penalties were applied in the case of constraints violation [59]. In the two-loop network, the results were identical to the ones obtained by the SCE algorithm of Liong and Atiquzzaman [88]. For the New York City Tunnels, the HS was the algorithm that demonstrated the best performance, presenting the lowest cost for the network with a significantly reduced CPU time when compared with the methods mentioned before. The solution obtained for the Hanoi case was the same as the one obtained by Cunha and Sousa using the SA (Cunha and Sousa, 1999 *apud* [59]) and by Cunha and Ribeiro using the Tabu Search approach [34]. In the case of the networks in South Korea, the HS demonstrated a similar performance compared to a GA and a better performance than an algorithm based on the NLP [59].

Later, in 2009, Geem tested the HS algorithm in a network containing a pump [60]. The objective function included not only pipe capital costs but also capital and energy costs related to the pump. Also a penalty function, to solve pressure head constraints, was added for infeasible solutions proportional to the distance away from the feasible solution area. The same problem was solved by Costa et al. [31] using Simulated Annealing. The HS model found the same solution as the SA. However, HS demonstrated to converge faster in finding the optimal solution [61].

Particle Swarm Optimisation (PSO), developed by Kennedy and Eberhart [82], was tested in 2008 by Montalvo et al. [106] to optimise the design of the New York City and the Hanoi networks. Although good results were obtained, the Harmony Search algorithm of Geem [59] was still presenting the best performance for both the network benchmarks.

A modified harmony search algorithm incorporating particle swarm concept (Particle-swarm harmony search, PSHS) was proposed by Geem [60]. This hybrid concept was tested in three network benchmarks: two-loop, Hanoi and NYCT. The improved HS demonstrated to converge faster than the simple HS, however, it might converge too early. In the case of the two-loop and the Hanoi networks, the PSHS found the same optimum obtained with the simple HS, however faster. In the NYCT, PSHS also reached the solution quickly; however, the cost was slightly higher than the one obtained with HS [61].

Differential Evolution was also applied in this kind of problem. Vasan and Simonovic [148] tested the algorithm in the Hanoi and New York City problems, using EPANET 2.0 for the hydraulic evaluation in each iteration. In the Hanoi case, the same solution obtained previously with HS [59] and with Tabu Search [34] was found in a reduced number of function evaluations. For the NYCT, the DE algorithm took a significantly higher function evaluations number and only reached the same solution obtained with the PSHS algorithm (a near-global solution).

Recently, Bragalli et al. [13] optimised the Hanoi and the New York City water networks using a Mixed Integer Non-Linear Programming formulation (MINLP). The authors resorted to Bonmin [30], an open source C++ code for solving general MINLP problems, with a few modifications. The developed formulation allowed a faster achievement of the global optimum in the Hanoi case and the lowest cost function was found for the NYCT. Furthermore, the configuration of the solutions obtained by the approach of Bragalli et al. demonstrated to be ready for immediate use in practice, providing a correct hydraulic operation of the networks and a beneficial effect on water quality [13]. This characteristic does not usually occur in designs obtained by some meta-heuristic algorithms based on probabilistic approaches.

Some researchers have verified in practice that the constraints should not be so restricted and neither treated with penalties which can make the optimisation process difficult. Instead of that, they claim that some constraints should be treated as optimisation criteria, leading to the concept of multi-objective optimisation.

The Anytown problem was solved through a multi-objective approach, by Walters et al. [157], using the Structured Messy Genetic Algorithm, firstly introduced by Halhal et al. [71]. The methodology of Walters et al. [157] considered two objectives: minimisation of costs and maximisation of benefits resulting from a certain solution (these benefits were evaluated in terms of pressure and storage deficits reduction). In their approach, pumping and storage were included in the optimisation problem. The authors presented two selected feasible solutions (the cheapest and the preferred in terms of operational performance of the network) which demonstrated to be better than any previously published solutions for this specific problem.

Cheung et al. [25] provide a comparative study between the non-elitist Multi-Objective Genetic Algorithm (MOGA) and the elitist Strength Pareto Evolutionary Algorithm (SPEA). The two-reservoir problem was used to test the performance of distinct algorithms and the hydraulic evaluation was guaranteed by EPANET 2.0. In this work, the considered objectives were costs and pressure deficits minimisation. SPEA demonstrated to be faster than MOGA, requiring smaller processing time [25]. The best solution obtained using the multi-objective approach was even lower than the minimum obtained through single-objective approaches.

Formiga et al. [57] tested the fast elitist Non-dominated Sorting Genetic Algorithm (NSGA-II), suggested by Deb et al. [38], in the two-loop case with some modifications of the original problem including the use of the Darcy-Weisbach formula instead of the Hazen–Williams and the consideration of leakages in pipes. In this case, three objectives were considered for the optimisation of the WSS: minimisation of costs and leakages and maximisation of the reliability (represented by entropy and resilience). The best solution found was 7.4% superior to the lowest values obtained in previous works, although it might be due to the modifications of the original problem. Nonetheless, the algorithm demonstrated to be capable of finding a well-defined Pareto front in little more than fifty generations.

Farmani et al. [51] went further and tested the Anytown problem with an Evolutionary multi-objective optimisation method including pump operation schedules in the problem (for a 24-h period). Their approach included maximisation of the reliability (resilience only) and minimisation of the costs and residence time (to meet water quality standards). The function for the total cost was defined as the sum of pipe and tank capital costs and pumping operating costs. The cheapest solution found was superior to the one obtained previously by Walters et al. [157] also using a multi-objective approach. However, it has to be noticed that the conditions considered in both cases, such as the number of objective functions, were distinct, which affect the results. Anyway, the fact of Farmani et al. [51] have considered simultaneously the design and operation parameters, as well as included cost, reliability and water quality as objective functions, allowed achieving high quality solution networks capable of operating under five loading conditions.

Perelman et al. [120] proposed the application of the Cross Entropy (CE) methodology for multi-objective optimisation, firstly introduced by Rubinstein [127]. This methodology incorporates elements from multi-objective evolutionary algorithms and makes use of generated elite solutions for the CE probabilities update instead of use the values of best-fitness functions [120]. The approach was tested in the NYCT problem and was capable of reaching near-optimal solutions with zero maximum pressure deficits.

Olsson et al. [113] investigated three distinct algorithms based on the Building Blocks strategy for multi-objective design of WSS: (1) Univariate Marginal Distribution Algorithm (UMDA), (2) Hierarchical Bayesian Optimisation Algorithm (hBOA) and (3) Chi-Square Matrix (CSM). The building block identification was one of the strategies tested before by Wu and Simpson [160] in a single-objective approach (also cited above). The NSGA-II, introduced by Deb [38], was also used in this work and compared jointly with the other three algorithms. The NYCT and the Anytown were the benchmark problems tested for this comparative study. In the NYCT case, only the NSGA-II and the UMDA were able to find the minimal cost solution (zero cost due to no duplication of any pipe). The hBOA and the CSM presented poor Pareto front coverage. The best zero deficit solution was found by the NSGA-II [113]. With respect to the Anytown case, the UMDA and CSM presented the lowest solutions with zero deficits. Olsson et al. [113] concluded that the loss of front coverage for small problems make the building blocks identification algorithms unsuitable. However, for large problems, these algorithms outbalance the coverage problem and offer serious advantages over the NSGA-II [113].

To finalise, it should be pointed out that some studies, especially the ones applying classic algorithms, tend to oversimplify the problems in order to make the application of several optimisation techniques in distinct WSS possible. However, it is very important to focus not only on the performance of the optimisation algorithms but also, primarily, on the details of the design problem without forgetting essential elements in order to always ensure the proper operation of the networks.

Kang and Lansey [81] provide a study that demonstrates the importance of not only considering the transmission mains when optimising the design of a WSS but also including the distribution mains. The authors verified that the simplification of the systems ignoring the local distribution pipes results in oversized optimised systems, followed by excessive pressures. The only difficulty of including local distribution pipes is the increase of the problem complexity. However, to solve this, Kang and Lansey [81] propose a methodology that consists of fixing the local pipes size at their minimum allowable diameters. This strategy allows the inclusion of local distribution pipes in the models without the increase of the number of decision variables.

With respect to the performance of the optimisation algorithms, Kang and Lansey [81] also proposed an approach to improve the convergence of GAs in order to obtain good solutions with much less computational effort. Their approach is based on the generation of logical initial populations using engineering judgement instead of the typical random generation. Results showed a consistent optimised pipe layout using this heuristic approach and an inconsistent optimised layout using the random generation.

4.2. Control optimisation

The WSS control operations can be included in design optimisation problems. However, due to the burden of operational costs in the total cost of a WSS, the control optimisation can emerge as a particular optimisation problem.

The optimisation of the WSS operation consists of finding the best strategies for the control elements, minimising the total costs while satisfying the consumers demand in terms of flow and pressure conditions [23]. In several scientific works, the control optimisation problem is treated as a single-objective problem consisting of the minimisation of the operational costs and the use of constraints to satisfy the WSS requirements. However, other works also look into this kind of problem as a multi-objective optimisation problem: minimisation of costs and maximisation of hydraulic benefits [130,18,94], in resemblance to what was shown previously for design optimisation.

A control optimisation strategy can also be static or dynamic when real-time systems are used simultaneously [33]. Real-time control approaches are discussed in Section 4.2.2.

Control optimisation models have been proposed since the seventies, exploring several optimisation techniques such as the most traditional (i) Linear Programming [151,150,55] and (ii) Nonlinear Programming [150,23,14,24,107], but also the meta-heuristics derived from nature such as (i) Genetic Algorithms [98,129,18,123,134], (ii) Simulated Annealing [134,68], (iii) Ant Colony Optimisation [90], etc. Genetic Algorithms and mainly Hybrid Genetic Algorithms [147,134] have stood out for their strong ability to solve optimisation problems with high level of nonlinearity and also for their performance dealing with the multi-objective optimisation perspective.

In the literature, the most used water networks benchmarks for control optimisation are mainly: (i) the case-study of Van Zyl, (ii) the Richmond network in UK, (iii) the network of the city of Austin in Texas and (iv) the North Marin Water District in California.

4.2.1. Pumping systems

In WSS, pumping energy costs usually represent the main costs of the water companies [147,150]. Pumping systems represent nearly 20% of the world's energy used by electric motors and 25–50% of the total electrical energy required in some industries [74]. All these facts imply an increasing demand to control pumps efficiently by the water industry.

Inefficient pumps, inefficient pump combinations and inefficient pump scheduling are the three main problems that are commonly found in pump stations. Thus, the use of optimisation techniques for the improvement of the pumping systems is crucial, either for the optimal schedules computation or for the optimal combinations.

Pumps can be controlled according to variations in suction pressure or even by time controls [52]. However, in most of cases, pumps are controlled by the reservoirs water level variations. In these cases, pumps are only switched on when the reservoirs responsible for supply certain populations are empty (or in the minimum level) and switched off when the same reservoirs reach the maximum level allowable. If the pumps are operated according to the variation of the energy tariff during a day and according to the water consumption patterns, then the associated costs would be significantly reduced [26].

When optimising the pumps operation it is possible to obtain not only energy savings but also better performances, improved reliability and even reduction in life cycle costs [74].

Nowadays, there are a large number of scientific works dealing with operational pump optimisation, usually referred to as pump scheduling optimisation (as, for example, [130,146] etc.)

In the literature, there are essentially two kinds of explicit pump control optimisation problems: (i) the most common one deals with constant speed pumps, where only two solution variables are considered for the pump operation (with the values 1 or 0, usually representing the pump status switched on or switched off), and (ii) the other deals with variable speed pumps,

where the values of the optimisation variables are defined by the set of speeds of the pump. In some cases, pump operating times are also used for the explicit formulation of the optimisation variables [115]. Some works also investigate the operational optimisation of the pumping systems through the perspective of other elements of the network (implicit formulation), where the decision variables can be represented by the reservoir levels variation, the pump station discharge or the supply pressure.

Typically, to solve this kind of problem, simulation periods of 24 h with 1-h time-steps are used. However, Bene and Hős [11] had demonstrated with their study of least-cost filling reservoir that the choice of time-steps smaller than 1 h can provide better results. The main conclusion of their work was that by fixing a temporal time-step and sequentially setting the pump operating point (minimal energy consumption), a globally reservoir filling policy can be realised. However, the technique loses its optimality if the energy tariff or the consumption changes during the optimisation process [11].

Ormsbee et al. [116] provided three mathematical formulations for pump scheduling to minimise the associated energy costs, described by: (1) an implicit formulation, where the decision variables can be the pump stations discharge, the tanks water levels or the pressure and then, the pump schedule associated to the obtained solution need to be found; (2) a discrete explicit formulation, where the number of decision variables is given by the product between the number of pumps and the time intervals in which each pump operates (these time intervals can be restricted or unrestricted, i.e., can be restricted to some periods of the simulation time horizon or can include the entire time horizon); and (3) a composite explicit formulation, in which a single decision variable for each pump station is attributed. These formulations can be solved through unconstrained methods applying penalties or through constrained methods where the constraints can be directly incorporated in the algorithm [116].

The gradient-based optimisation methods were the first to be tested for pump scheduling optimisation [23,14] and then, the nature-based algorithms became to surge [98,130,67], demonstrating to be more adequate since there is no need of over-simplification of the problems used. In the last ten years, a large variety of studies applying a number of distinct meta-heuristic algorithms combining global and local search techniques, which tend to improve the convergence of the methods, have emerged.

The works of Cembrano et al. [23] and Brion and Mays [14] are examples of well-succeeded applications of classic algorithms for the pump schedules optimisation.

Cembrano et al. [23] tested the Conjugate Gradient method in the Barcelona network (Spain) using a single-objective approach to minimise operational costs considering decision variables such as the flow combination provided by the pump stations, valves or turbines (continuous variables). Although the Barcelona network is composed of 4 sources, 5 valves, 7 pump stations (of fixed-speed), 2 turbines, 11 demand areas with distinct pressure zones and 11 storage reservoirs, a linear model for the dynamic behaviour of the system was considered. State and boundary constraints were considered by the authors and penalty functions were used in the case of constraints violation. Their model was able to find optimal schedules for the pumps and optimal valves control capable of reducing the operational costs associated. The optimised operational results obtained were similar to the one obtained in a previous work using Dynamic Programming. However, the computational effort required by the latter methodology was lower [23].

Brion and Mays [14] resorted to the KYPIPE computer programme to optimise the operations of the Austin network (Texas) which comprises 1 pump station with 3 parallel fixed-speed pumps, 8 pressure zones and 2 storage reservoirs. The model applies a Generalised Reduced Gradient algorithm and an Augmented Lagrangian method for the application of penalties. Considering a time horizon of 24 h divided into 12 2-h time-steps for the pump schedules, Brion and Mays obtained a reduction of 17.3% in the Austin operational costs [14]. The authors verified that the algorithm used were very sensitive to the Lagrangian coefficients.

The network of the city of Austin was later optimised by Goldman and Mays [67] using Simulated Annealing (SA). Constraints to the tanks levels, to the nodal pressures, continuity and water quality were taken into account in their optimisation process. The pump operational costs were reduced 4.1% by taking twice the number of iterations required by a Nonlinear Programming (NLP) method. The costs reduction was quite small, however, it should be noticed that additional constraints were included. At the same time, SA demonstrated to be more flexible and adaptable than NLP, providing a number of optimal pump schedules instead of only one [67]. The same model was also applied to the North Marin Water District network (California), comprised of 2 sources, 2 fixed-speed pumps and 3 tanks, and demonstrated once again a good performance in finding optimal pump schedules [67].

The good performance of the Genetic Algorithms (GA) applied to the operational optimisation of a WSS was soon demonstrated by Mackle et al. [98]. The authors tested this algorithm in a simple network containing one source, four parallel fixed-speed pumps and a single storage reservoir. Considering continuity and reservoir water levels constraints, an optimised pump schedule adapted to the energy tariff was obtained in just 20 min (10,000 generations).

The network of Richmond (UK) has been a subject of many control optimisation studies [8,147,92,93]. This benchmark network, presented in Fig. 2a, is composed of a unique water source, a pump station containing two parallel fixed-speed pumps, five booster pump stations (with a single pump each), six tanks and distinct pressure zones.

In 2000, Atkinson et al. ([8] *apud* [147]) reduced 19% of the operational costs of the Richmond network using a commercial hydraulic simulator and GAs. However, due to the burden of the simulator, the computational time was extremely high (69 h).

Later, Van Zyl et al. [147] developed a hybrid optimisation strategy, combining Genetic Algorithm with two types of Hill Climber methods: (i) Fibonacci coordinate search and (ii) Hooke and Jeeves pattern search. As the GA is efficient in identifying the region of the optimal solution but less efficient in finding the optimal point in that region, the introduction of a technique like the Hill Climber can improve the local search. In this study, the optimisation variables were defined in terms of tank level controls. A pump penalty cost and a tank penalty cost were used to impose the system constraints (tank water levels and number of pump switches). These penalties were determined by a *trial and error* approach. Applied to the Richmond network, the hybrid method proved to be superior than the pure GA, reducing more than 25% of the operational costs. The developed methodology was also applied to a particular case study (see Fig. 2b), introduced by the authors, comprising 1 water source, 1 pump station (2 parallel fixed-speed pumps), 1 booster pump station (1 pump) and 2 tanks. Also in this case, the hybrid GA performed better than the pure GA both in convergence speed and quality of solutions [147]. The best results obtained for the hybrid algorithm were with the Hooke and Jeeves technique. The greatest difficult in this work, as referred by the authors, was to decide when to change from the GA to the Hill Climber method. This is a typical difficult task to solve for those who work with more than one optimisation algorithm.

Comparing their work with the ones previously published by Atkinson et al. ([8] *apud* [147]), Van Zyl et al. stated that the same reduction of 25% could be obtained using the methodology of Atkinson et al. if the constraint for the 95% full requirement of the tanks have been applied at 7:00 instead of 5:00. This issue related to the ideal initial water level in tanks presents a significant

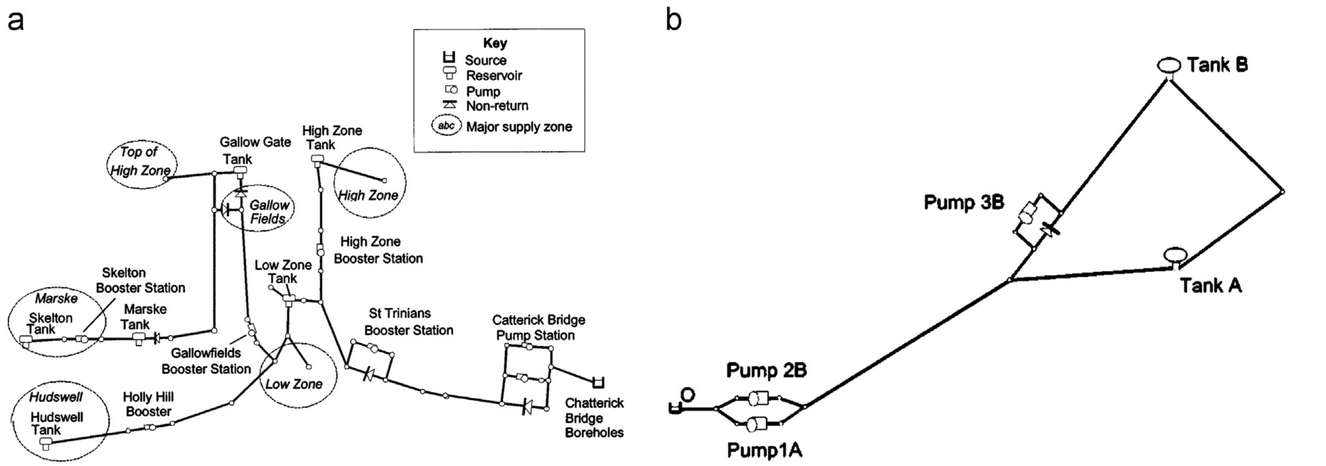

Fig. 2. Representation of the most tested benchmark water supply networks for control optimisation: (a) the Richmond water network and (b) the Van Zyl network case-study (both adapted from [145]).

influence on the control optimisation problems. However, the ideal level can be distinct from one case to another since it depends, for instance, on the energy tariff and on the water consumption. Thus, it should be important to carry out sensitivity analysis on this variable for each tested network.

Trying to reduce the computational effort of the optimisation problem in the Richmond network, López-Ibáñez et al. [92] proposed the use of a parallel Ant Colony Optimisation (ACO) technique instead of the common sequential technique, i.e., instead of a sequential iteration between ants during the optimisation, the authors propose the iteration through some threads in parallel. EPANET library was then combined with a parallel ACO algorithm. Results of the application of this methodology in the Richmond network showed that the optimal solution was found in 8000 iterations (the same required by the hybrid GA of Van Zyl et al. [147]) consuming less than half an hour, while using a sequential technique would take around 2 h. The authors also verified that, in the parallel ACO, a higher number of ants reduced the computation time, which is the opposite in the sequential ACO. Another advantage of the high number of ants is the possible improvement of the final solution.

A study comparing three distinct representations of the decision variables for fixed-speed pumps is provided by López-Ibáñez et al. [93], in which both methodologies were tested in the case-study of Van Zyl et al. [147] and also in the Richmond network. The authors compared (i) the common binary representation, (ii) the level-controlled triggers and (iii) the time-controlled triggers representations using the Simple Evolutionary Algorithm (SEA) linked to EPANET. The violation of the constraints related to tanks water levels, continuity, nodal pressure head, number of pump switches and to the occurrence of warnings on EPANET were handled by a method based on ranking solutions with respect to the constraint violation [93]. Globally, the SEA with time-controlled triggers demonstrated better performance when compared to the SEA with both binary and level-controlled triggers or even compared to the Hybrid GA of Van Zyl et al. [147], also using level-controlled triggers. It should be worthy to notice that López-Ibáñez et al. [93] believed that adapting the hybrid GA of to the time-controlled triggers may further improve the results.

The case study of Van Zyl et al. [147] had also been analysed by López-Ibáñez et al. [91] using a multi-objective approach with the SPEA2, a second version of the Strength Pareto Evolutionary Algorithm coupled with EPANET 2.0. Their model conjugates a number of improvements that had been implemented in other works using multi-objective approaches. The objectives considered in this model were the minimisation of both the costs and the number of pump switches. Constraints for tanks water levels and nodal pressures were handled by a method based on ranking solutions with respect to their constraint violations. Results demonstrated that, considering a 24-h horizon (1-h time-steps) and using a binary encoding of the decision variables, better solutions are obtained when compared to the same approach for a single-objective optimisation [91].

Other works have also been presenting the performance of other optimisation algorithms and innovative techniques. However, it is notorious in the lack and, consequently, the need for comparison of some of these methodologies in benchmark networks in order to obtain more valuable results.

For a case study in Brazil (Goiânia network), Carrijo et al. [18] used the SPEA connected to EPANET 2.0 for the minimisation of operational costs (pumps and valves) and the maximisation of hydraulic benefits (evaluated through indexes for pressure requirements, demands and reservoir levels). In this work, the use of data mining to extract operational rules for the system is also introduced in order to reduce the dependence on experts for the choice of the most adequate solution in the obtained Pareto front.

The work of Lücken et al. [94] offers a comparative study using sequential and parallel implementations of six distinct Multi-Objective Evolutionary Algorithms (MOEAs): (1) Multiple Objective Genetic Algorithm (MOGA); (2) Niched Pareto Genetic Algorithm (NPGA); (3) Non-Dominated Sorting Genetic Algorithm (NSGA); (4) Strength Pareto Evolutionary Algorithm (SPEA); (5) NSGA-II; and (6) Controlled Elitist NSGA-II (CNSGA-II). The objective of the work consisted on the minimisation of (i) energy cost, (ii) number of pump switches, (iii) maximum power peak and (iv) reservoirs levels variation [94]. Parallel implementation of MOGA, NPGA and NSGA do not find any non-dominated Pareto solution. On the other hand, the best position was obtained by the parallel implementation of CNSGA-II using 16 processors [94]. The authors identified several improvements of their parallel strategy over sequential MOEAs [94]: (i) exploration in larger areas due to a larger number of population; (ii) introduction of cooperation between populations which helps in the search for good solutions; and (iii) inclusion of a process for elitism reinforcement, preserving solutions that could be lost.

Wang et al. [158] were the first researchers to consider the land subsidence due to groundwater pumping all day long, which can be solved using intermittent pumping. In their model, a Genetic Algorithm is used for the minimisation of both pump operational cost, number of switches and total work time for each pump.

Constraints to control the reservoir levels and the flow in the system, to avoid underflow or overflow, were handled with penalty functions. The model also includes local search for the improvement of the solution quality and the pump control was performed by time interval representation using a real-number array instead of a binary bit string. A number of possible solutions with lower electricity cost and, at the same time, with eco-aware schedules were achieved. However, the authors considered that the convergence speed could be improved [158].

Firmino et al. [55] used a two-stage optimisation method based on Linear Programming and Integer Linear Programming by an optimisation toolbox of MATLAB 7. This method was applied to Campina Grande WSS in Brazil, containing three pumping stations, and has saved around 15% of the costs and energy consumption (single-objective approach). Constraints to the reservoirs levels, to the maximum allowable pump flow and for the guarantee of periodicity of the schedules (continuity) were considered.

A case study in China [134] of a large-scale WSS, containing fixed- and variable-speed pumps, demonstrated a reduction in energy costs of 6.04% using a Hybrid Genetic Algorithm called Genetic Simulated Annealing (GSA) for the optimisation of the pump schedules. The developed methodology considers a single objective function which includes not only electricity cost of pumping but also the water production cost. Constraints to the tanks water levels, continuity, velocity limits of the variable-speed pumps and also the number of pump switches were considered [134]. It has to be noticed that this problem deals with both the fixed- and variable-speed pumps, which implies distinct decision variables and increases the complexity of the optimisation problem. At the same time, a good algorithm for the optimisation of fixed-speed pump schedules could not be adequate in the case of variable-speed pumps. This topic was not yet analysed in detail in previous works and it is of large importance since most actual WSSs can be constituted by distinct kinds of pumps.

Recently, Mouatasim et al. [107] proposed the use of a reduced gradient algorithm for the problems of Kénitra and Agadir cities in Morocco. Their methodology based on the algorithm called Stochastic Perturbation of Reduced Gradient (SPRG) was compared with the optimisation solver LINGO. The objective function considered is the sum of the cost function of every wells and treatment plants existent in the networks. The pumps were only allowed to operate in three time periods of the 24-h horizon. Results for both networks indicated a significantly better performance of the SPRG compared to the LINGO solver [107].

Also Coelho et al. [27] provided a work comparing distinct optimisation algorithms applied to water networks evaluated using EPANET 2.0. The authors tested three distinct algorithms:

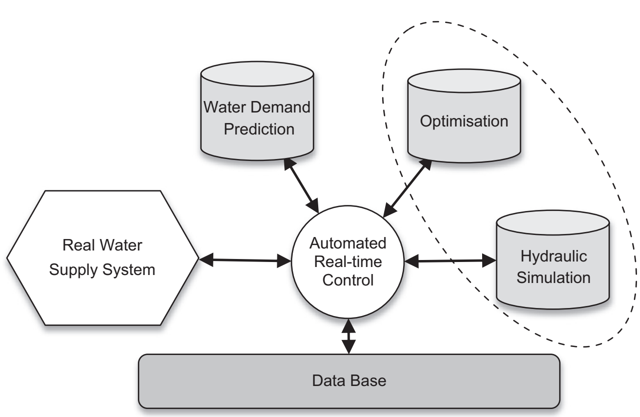

Fig. 3. Scheme describing the optimal operation of a Water Supply System using a SCADA system.

(i) an Evolutionary Algorithm (EA), (ii) a gradient-based algorithm and also (iii) an hybrid algorithm, called HDEPSO [20], which combines Differential Evolution (DE) with Particle Swarm Optimisation (PSO). The operation of variable-speed pumps during a time horizon of 24 h was optimised taking into account the water consumption of the population and the variation of the energy tariff.

4.2.2. Real-time operations

A Supervisory Control and Data Acquisition (SCADA) is a system also used in Water Supply Systems for the real-time control and monitor of several elements such as pumps, valves, reservoirs, etc. [156]. Real-time strategies allow optimal operational adjustments to possible variations in the networks such as sudden fluctuations in demand, contributing for the efficiency improvement of the WSSs.

According to Gellings [62], the potential savings from the use of SCADA systems are from 10% to 20% of total WSS energy consumption. Making the system automatic, efficiency is increased and a reduction on costs occurs.

A SCADA is basically a system composed by one or more field data interface devices such as reservoir level metres, water flow metres, valve position transmitters, power consumption metres and pressure metres [156]. All the system must incorporate [156]: (i) a central host computer server (or servers), (ii) a type of communication to transfer data between field data interface devices and the computers of the central host (radio, cable, satellite, telephone, combinations of these or others), and (iii) a software to allow central host and terminal operator applications and to support the communications and the devices. Thereby, the main functions of a SCADA system are (1) data acquisition, (2) data communication, (3) data presentation and (4) control.

Fig. 3 shows an example of a scheme for the optimal operation of a WSS using a SCADA system. The scheme incorporates modules for water demand prediction, optimisation and hydraulic simulation. The automated real-time control system allows data management and the transmission of information between both modules and the WSS that is intended to be optimised. A data base is also necessary to record the history of water consumption and all the characteristics of the real network.

A large number of works dealing with real-time operational optimisation of WSSs were already published (e.g. [123,126,94,16,24,32]).

Fallside and Perry [50] and Coulbeck et al. [32] were some of the first researchers publishing in this area.

A similar scheme to the one represented in Fig. 3 is presented by Coulbeck et al. [32], describing with more detail the basic modules (prediction, optimisation and simulation) and procedures for the successful implementation of a real-time completely automated optimal control strategy. The prediction module (called GIDAP, in this case), integrating demand analysis and prediction, involves distinct processes [32]: (i) screening of the telemetered data (error values are replaced by interpolation or previously predicted values); (ii) data smoothing, to remove possible disturbances; and (iii) trend estimation, for the demand estimation through the use of screened and smoothed data. More details about demand prediction can be consulted in Section 4.2.3. In the optimisation module (called GIPOS for a single water source and GIMPOS for multiple sources), pumping and storage are controlled by the computation of optimised pump schedules taking into account constraints of the reservoirs water levels, the consumers demand (provided by the prediction module) and also the general constraints related to the system operation [32].

The success of the optimisation procedure has a strong dependence on the hydraulic model of the system. In some cases, the system model can be incorporated in the optimisation procedure

although it tends to become oversimplified. For this reason, the recourse to a hydraulic simulator is usually desirable for providing a better approximation of the system performance. At the same time, the hydraulic module can be used to compare the actual performance of the real network with the performance after optimisation and also used for non-routine or emergency situations [32].

The typical data transferred by the SCADA systems comprise [32]: pump and pipe flows, pressures, control states and reservoir levels. System monitoring, usually carried out by means of telemetry, is required to guarantee the correct operation of the network since regulatory actions are dependent on the predicted behaviour of the system under a set of conditions [32].

Coulbeck et al. [32] also refers the importance of a unique data base, which allows the combination between the recent telemetry information and all the other data required for the individual modules.

The real-time control scheme of Coulbeck et al. [32] was implemented in a network in the United Kingdom providing not only automatic least-cost pump schedules but also instantaneous system assessment and automated system operations.

Fallside and Perry [50] introduced a hierarchical approach for the online optimisation of a water supply network. This hierarchical approach consisted firstly the use of linked computers, one for optimisation calculations and the others for data measurement and system control (decentralised optimum computer control). Secondly, the optimisation process was based on a hierarchical decomposition technique employing the Lagrange duality theory. Basically, the dual of the original problem is formed and then, a decomposition technique allows obtaining a set of smaller and independent problems easier to solve through a standard method.

The methodology of Fallside and Perry [50] was applied to the East Worcestershire system that operates 7 source stations, 5 spring sources, 15 pressure boosters, 21 service reservoirs and 6 water towers. Pumps were operating in fixed- or variable-speed to maintain the best efficiency in the operating range. The system was also provided an automatic control consisting on a central computer connected to all major elements of the system by radio or landline. The control system was able to provide information about 200 elements every 65 s [50].

The developed hierarchical techniques allowed essentially the reduction of the computational burden [50].

Cembrano et al. [24] developed an online optimal control tool using an optimisation solver called WATERNET and other management tools for simulation and quality control, both linked to a SCADA system. The developed user interface allows the easy control optimisation of distinct water networks. The methodology of Cembrano et al. [24] consisted the use of a Generalised Reduced Gradient algorithm for the real-time optimal valve and fixed-speed pump controls. The entire control system was then composed by an optimiser, a demand forecast and a SCADA system. This type of control was tested in a prototype of the network of Sintra (in Portugal), resulting in a total cost reduction of around 18% [24].

Pegg [119] showed the implementation of the Derceto's computer programme[1] for the operational optimisation of the Wainuiomata-Waterloo network (Wellington), which comprises 3 water treatment plants, 12 reservoirs, 5 fixed-speed pumps (4 standby), 2 variable-speed pumps (1 standby), 1 dual-speed pump (standby) and 1 control valve. The programme was set to run every half-hour and previous solutions were maintained until a new one was provided.

For the real-time control, Pegg [119] implemented Derceto's programme in a computer, running WindowsNT and linked to the control system responsible for provide telemetry information. The selected operator interface was a SCADA system called Citect (for more information about Citect see [133]).

The main steps in Derceto's programme operation includes [119]: (1) initialisation of system data, (2) determination of the mass-balance required to get all the reservoirs full at the end of the day, (3) computation of the lowest cost schedules and (4) checking of the results using the simulator EPANET. These stages typically run several times to improve the accuracy and then, the information is passed to the telemetry or central control system.

Pegg results demonstrated a reduction of approximately 10%. in the energy cost of the Waterloo network During the real-time implementation, some events such as (i) pump failure, (ii) pipe maintenance, (iii) telemetry failure or (iv) systematic errors on metered data have occurred. However, the used programme was able to deal with the unusual situations by quickly adaptating to the unexpected changes [119].

Later, a work containing results of the real-time optimisation using Derceto's programme (Aquadapt) in two distinct cases was provided by Bunn [16]. The tested systems were the East Bay Municipal Utility District (EBMUD) and the Washington suburban system. EBMUD already had a centralised pump scheduling package which facilitated the application of Aquadapt, allowing energy cost savings of 13.1%. The case of the Washington suburban system presented more difficulties in the interface because there was no centralised Programmable Logic Controller (PLC). Thus, the existent Remote Terminal Units (RTUs, also referred as Remote Telemetry Units) were replaced by smart LPCs. Results showed energy cost reductions up to $1000/day in the third week of implementation [16]. All these savings were obtained by (i) moving energy use to cheaper periods, (ii) reducing peak demand charges and (iii) reducing the energy required for pumping [16].

Although PLCs have similar functionalities as RTUs, they present the advantage of combining large quantities of digital and analogue data and producing algorithms of high complexity [16]. On the other hand, an RTU usually does not support control algorithms or control loops.

The JEA's Operation Optimisation System (OOS) project presented by Barnett et al. [10] is another case incorporating demand forecasting, modelling, simulation and optimisation coordinated by a SCADA system. The hydraulic model used in this project was the WaterGEMS (referred in Section 4.2) and its calibration was through historical samples and real-time data from the Jacksonville water network (Florida, USA). This network, composed of 32 wells, was also used for testing the real-time OOS. The automatic model developed in this project included techniques such as [10]: (i) neural networks for consumption prediction, (ii) nonlinear constrained optimisation for pump and valve schedules and (iii) mechanistic hydraulic and mass-balance for water supply modelling.

The most significant improvement in the Jacksonville network provided by the real-time optimisation was the capital costs reduction. Energy savings and water quality improvement were also identified and, moreover, the return on investment for this project was less than one year [10].

The POWADIMA research project [123] has developed a real-time methodology which combines the use of an Artificial Neural Network (ANN) for predicting the consequences of different pump and valve control settings (hydraulic behaviour) and a GA optimiser for selecting the best controls combination. Constraints to pressures, flow velocities and reservoirs levels were also included. A SCADA system was responsible for providing data updates after

[1] Currently, the Derceto programme is called Aquadapt (a reference to this programme is provided in Section 4.2).

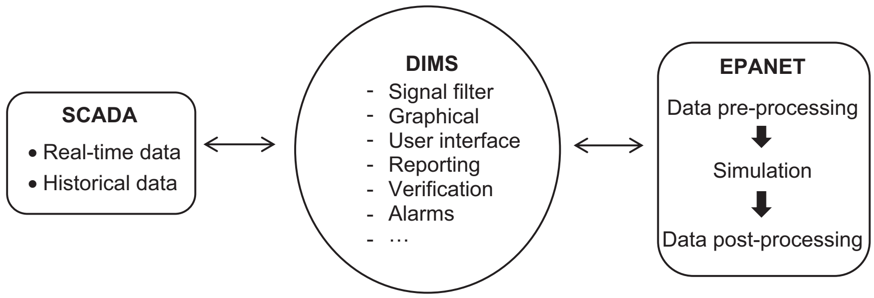

Fig. 4. General scheme of the online EPANET solution presented by Ingeduld [78].

every 24 h. This methodology was applied in the Haifa-A WSS of Mount Carmel, comprising 9 storage reservoirs and 17 fixed-speed pumps (5 pump stations), reducing in 25% the energy costs [128]. The Valencia WSS (Spain), containing 10 fixed-speed pumps (3 standby), was also tested, indicating an operational cost savings of 17.6% [101]. Comparing the same methodology combined with EPANET for the hydraulic behaviour verification instead of the recourse to the ANN, it was verified, for the Haifa-A case, that the GA-ANN model was approximately 25 times faster than the 112-node GA-EPANET model [128].

Ingeduld [78] investigated the use of EPANET on real-time operations. According to the author, linking a SCADA system to the hydraulic simulator EPANET allows the water network to operate into the following modes [78]: (a) Virtual-Sensor Mode, based on the WSS conditions which provides information about locations without measurements; (b) Hindcasting Mode that allows to obtain simulations of past events in the network; (c) Event-Simulation Mode that provides the response of a system when a specific modification is applied; and (d) Predictive Mode that provides a prediction of the system behaviour for a certain time horizon. These are the main advantages provided by the connexion between a hydraulic simulator and a real-time system.

To provide data transfer between the SCADA system and the hydraulic simulator, Ingeduld [78] pointed out the use of a Data Integration and Management System (DIMS) based on a SQL (Structured Query Language) client-server (see Fig. 4). The data communication is provided by online hosts and data drivers.

The online solution presented by Ingeduld [78] was applied in two case studies: (i) one at Czech Republic and (ii) another at Libya (specifically in the well-known Great Man-Made River project). In the first case, a SCADA SCX system and the MikeNet (see Section 4.2) were used. For the Great Man-River project, a Siemens SCADA system was selected for the data collection. In the second case, updates every 5 min and consequent analysis of the system were executed. Furthermore, historical data analysis and prediction of the system behaviour for the following 72 h were also performed.

The work of Machell et al. [95] also provides an insight about online modelling of WSSs and demonstrates its potential to detect events in the networks like ruptures. The authors used the AQUIS software (Section 4.2), an industry standard modelling package in the UK, that receives, every 30 min, flow and pressure data in real-time obtained by a GPRS communication. The online model was linked to DataManager, a database for configuring, pre-processing and administering that allowed to check out for missing and corrupt data [95]. The online model based on a SCADA system, applied to a UK case study, demonstrated to be able to provide early warnings of effects in each pipe of the networks and information about which customers were affected [95].

Dötsch et al. [46] provided a decentralised approach for the real-time control of a WSS. This approach consists of the communication between equipment (called agents) installed at each pump and tank of the WSS for the minimisation of energy costs associated to their operation. For the self-organised and decentralised coordination of the agents communication, the authors have resorted to a chemical stimuli strategy based on a biological phenomenon applied by plants to keep the herbivores away [46]. Two variants of their approach were compared [46]: (i) Greedy Mode (GM), the simple variant where the solution is based on the switch on and off of the pump nearest to a tank; and (ii) Coordinated Greedy Mode (CGM), a variant where the pump agents compare all possible solutions according to additional expected costs information and choose the most efficient one . Experimental results, using EPANET for the hydraulic evaluation of the networks, demonstrated that both variants provide optimal solutions. Moreover, it was also showed that in the CGM, more cost efficient controls can be obtained when additional information is provided to the agents [46].

4.2.3. *Water demand prediction*

An accurate estimation of water demand is an important requisite for the optimal operation and design of a WSS. The prediction of water demand allows better approximations between the water supply flow rate and the water consumption flow rate, providing more resource savings and, consequently, more cost savings [84].

Walski et al. define three basic water demand types [155]: (1) customer demand, the water required by the users in the system, (2) unaccounted-for water, related to water losses, unmetered services or other causes and (3) fire flow demand, the required system capacity to ensure protection during fire emergencies. Moreover, the authors refer that the process of establishing consumption rates requires studying of past and present usage trends and, sometimes, the projection of future ones [155].

The total water demand is characterised by time-varying (according to daily, weekly, seasonal and long-term scales), periodic and non-stationary series [6]. Current water consumptions are determined by a large number of industrial, commercial, public and domestic consumers [6]. Thus, the typical demand types are usually defined as [78]: (i) residential, (ii) commercial, (iii) industry, (iv) agriculture, (v) irrigation and (vi) leakages. Deviations caused by weather effects (temperature, humidity, wind, precipitation…), season effects (winter/summer) or even network effects (like pipe breaks) can be the reason of failure in some demand predictions [84].

Thus, for the water demand forecasting, socio-economic and climatic variables are usually needed [80]. While the climatic variables as air temperature or rainfall affects the short-term seasonal variations on demand, the socio-economic variables like water price, population or housing characteristics are responsible for long-term effects [80].

The most considered demand events are usually: (i) average day demand, (ii) maximum day demand, (iii) peak hour demand and (iv) maximum day of historical record [155].

Essentially during the peak periods, where higher demands are expected, re-evaluations of new demand profiles are usually more necessary [32].

For the development of a database, the water usage information can be collected by distinct forms [155]: (i) flow information, like the rate of production of a treatment system, (ii) volumetric information, provided, for example, by the client water consumption or (iii) hydraulic grade information, such as the level variation in a tank. All the information should be recorded into an accessible format in order to facilitate the process of data loading into a hydraulic model [155].

Typically, the most developed models provide 24-h patterns of demand prediction for a number of consumption points in each control area. The predictions are usually extrapolated from current water consumption and recorded data. A number of prediction strategies resorting to fuzzy logic and/or artificial neural networks have also been tested [87,80,36].

The advantage of forecasting models based on fuzzy logic or neural networks is to provide multiple points of data as long as enough historical data are available for training [87]. On the other hand, time series analysis, like auto-regressive models, do not require pre-training, but only provide a prediction of a few data points [87].

An et al. [6] proposed the use of a method called data mining (automated learn from observed data) for daily water demand prediction. The main objective of this work was to provide a technique for generating prediction rules from incomplete information. The authors used a database containing environmental and sociological information and the daily volume of distribution flow. Eighteen condition factors for water demand prediction (day of week, temperatures, humidity, etc.) were selected from the many existent. These factors were obtained from a monthly meteorological summary and the historical information about water consumption has been recorded by summing the daily distribution flows metered at the pumping stations.

A set of training samples (observed data) was used by An et al. [6] for the generation of each classification rule (rough-set method). The training samples consisted of more than 300 objects projected for each condition attribute. The process of rules generation was based on the set of condition attributes that did not provide any additional information to the system and needed to be removed (condition attributes reduction). Such probabilistic decision rules were then used for the water demand prediction.

The methodology of An et al. [6] simply describes the relationships between condition factors and decision variables. The accuracy of the prediction can even be improved through the collection of more data [6]. It also should be noticed that the process of rule generation must be performed for each distinct network since the influence of each condition factor may differ from case to case.

As demand forecasters using a single approach tend to produce high prediction errors, Lertpalangsunti et al. [87] proposed the Intelligent Forecasters Construction Set (IFCS), a tool that supports the use of distinct techniques for demand prediction such as fuzzy logic, neural networks, knowledge-based and case-based reasoning. This hybrid approach, applied first on an electrical system for power demand prediction, is based on individual modules (one for each approach) that are combined using adaptive filtering schemes. The modular structure provides the possibility of integration with other intelligent modules [87].

The IFCS tool was implemented on a real-time system that supports rule representation, providing easy interpretations for the users [87]. A data analysis and processing module is responsible for preparing the data for the forecaster modules.

The methodology of Lertpalangsunti et al. [87] was tested in the city of Regina for the daily water demand prediction. Comparing the use of multiple neural networks with linear regression and a case-based reasoning technique, the lower percentage of prediction error was obtained by the multiple neural networks approach. Days of a week and temperature demonstrated to have a major impact on customer demand. Furthermore, multiple neural networks that separate the data daily in a week generate better prediction results. Finally, the authors concluded that the use of multiple modules of predictors allows obtaining better results than using the single prediction models [87].

The work presented by Jain et al. [80] provides a model for short-term water demand forecasts through the use of climatic variables such as the total weekly rainfall and the weekly average maximum air temperature in addition to the past water demands. Distinct techniques to model the weekly water demand were developed for comparing: (i) 6 back propagation ANN models, (ii) 5 regression models (linear and nonlinear), and (iii) 2 time-series models. Both techniques were applied at the Indian Institute of Technology at Kanpur. Results demonstrated that models based on ANN consistently outperformed the other conventional techniques of regression and time-series analysis, presenting an average absolute error in forecasting of 2.41% [80]. The authors realised that the water demand process of the case study was mainly driven by the maximum air temperature and interrupted by occurrences of rainfall. Moreover, they noticed that the occurrence of rainfall was a more significant descriptive variable than the amount of rainfall [80].

The project of Barnett et al. [10] (already described in Section 4.2.2) is another example of the application of neural networks for water demand prediction taking into account factors such as historical consumption and online data including weather forecasts. The input variables considered for the prediction in this project included: air temperature, dew point, wind speed, humidity, day of week and flow. The output of the neural network was the flow at each hour. Forecast errors equal or inferior to 15% were considered acceptable. The experimental results of Barnett et al. [10] demonstrated that the daily forecast error was less than 10%; however, the hourly forecast errors reached 50%. The authors also indicated that short-term forecasts across 4–6 h horizon presented smaller errors.

Cutore et al. [35] present a technique for dealing with prediction uncertainties from a daily ANN predictor model. The authors applied the Shuffled Complex Evolution Metropolis (SCEM-UA) algorithm for calibrating (training) the parameters of the three-layer ANN. The input vector of the ANN consisted of climatic data, system data and some indexes characterising the day of prediction. The SCEM-UA trained ANN was applied in the real-case of Catania (Sicily, Italy) and compared with: (i) an ANN trained by a Bayesian learning algorithm, (ii) a regression model and (iii) an adaptive network based fuzzy interference system (ANFIS). The predictive performance of the SCEM-UA ANN model was similar to the Bayesian ANN model. Compared to the 3 techniques the SCEM-UA ANN model present the advantage of better fitting the observed data in some calibration periods of time, providing more accurate water prediction [36].

A model of linear regression was applied by Vasilio and Jorge [149] to predict the daily water consumption of the Apucarana system (Brazil). The prediction model used seasonal and climatic historical data. Results revealed demand prediction errors from 0.01% (around 1 m^3) to 5.5% (almost 900 m^3) [149], which are also adequate values.

Works dealing with water demand prediction are generally compared to works of power demand prediction. However, it has to be noticed that, due to the common and large existence of noise in the data for water demand, the associated prediction errors tend to be superior.

With respect to the consideration of water demand uncertainty in problems of design optimisation, Babayan et al. [9] verified that neglecting the demand uncertainty can imply serious under-design of the networks. Therefore, it should be important to verify the effect of this uncertainty also for operational optimisation problems.

4.2.4. Systems with energy production

With the increasing introduction of renewable energy production in WSSs, the study of control optimisation techniques including possible new elements such as hydro-turbines or solar/wind-turbines is of high importance in order to keep the maximum energetic and economic efficiency of the systems. The implementation of optimisation strategies for the operational improvement of water supply systems containing such elements requires the availability of power forecasts, which can be possible to obtain, for example, trough time-series analysis or prediction algorithms based on neural networks or fuzzy logic [21].

The control problems of installations containing renewable energy sources are similar to the problems mentioned before. For pumps operating as turbines, for example, during the normal pump operation, both values of the characteristic curves (flow, head and speed) are positive; however, in the turbine mode, the discharge and speed present negative values [122]. Usually, pump manufacturers do not provide the characteristic pump curves when it operates as turbines [122].

Ouarda and Labadie [118] presented in their work the operational optimisation of a four-reservoir case study of Argentina (Hidronor river basin) containing hydropower plants. The authors used a chance-constrained optimal control resorting to Optimal Control Theory (OCT) that involves the use of ordinary and partial differential equations in continuous formulations [118]. This kind of formulation usually requires less computational effort than the typical Mathematical Programming (MP) techniques. At the same time, the presented technique is normally used for several continuous-time optimal control problems under constraints [118].

The main objective of the Ouarda and Labadie work [118] was the maximisation of the total energy production at hydroelectric plants. For that, two representations of the objective function were considered with the aim of evaluating the performance of the optimisation algorithm with distinct representations. The difference between both representations is that in the first, only the total energy production is considered and, in the second, the energy rate per turbine discharge is also considered [118]. Using the first representation of the objective function, a local optimum was obtained. The best values were achieved using increasing penalty weights (for the constraints violation) in multiples of five to fifty, leading to final objective values up to 96.4% of the true global optimum. Using the second representation of the objective function, the algorithm converges for the optimal optimum [118]. The authors have also considered measures for system reliability, considering a range from 5% to 95% (high to low theoretical risk) and the results provided optimal values reflecting several levels of reliability.

Teegavarapu and Simonovic [142] compared the performance of a mixed integer nonlinear programming with an improved simulated annealing (SA) technique applied to a real-time four-reservoir hydropower system in Canada. The considered improvements of the SA passed through repair strategies to generate feasible solutions for any configuration of the reservoir systems and heuristic rules to define the range of discharge variables [142]. The objective of the problem was to minimise the cost of power generation, considering half-day scheduling and 14 time intervals (1 week). A constraint is applied in order to guarantee that the total power demand by the reservoirs for both SA and MINLP models is the same (43 GWh). At the same time, discharge ranges are defined according to the variation of the generation cost. The SA model provided the best value for the objective function with less computational effort when compared with the MINLP formulation. The higher computational effort required by the MINLP is related to the high number of binary variables proportional to the number of time intervals. For both used techniques, it was also observed that the generation values were significantly higher for periods of lower generation cost [142].

Gonçalves and Ramos [69] proposed an optimisation methodology based on an economic analysis for the use of pumps as turbines (PATs). The main objective of this work was the identification of regions constituting potential for energy production in the WSS of the city of Aveiro (Portugal). Then, it was intended (i) to evaluate the available energetic potential, (ii) to calculate the energetic production, (iii) to study viability and economic analysis and, finally, (iv) to develope the optimisation proposal [69].

For the energetic potential evaluation, pressures and flows were analysed in five areas containing pressure reduction valves (PRV). All the hydraulic analyses were performed with the hydraulic simulator EPANET. The estimation of the energy production was based (i) on the head loss measured at each PRV using EPANET and (ii) on the demand prediction considering a population growth during 10 years [69]. Concerning to the economic analysis, for the possible flows and powers to install, the authors considered a criteria based on the Net Present Value (NPV) determined by the difference between the annual profits and the annual costs related to installation and maintenance, which allow increasing the profitability of the systems. For the optimisation of the system operation, considering the real-time consumption patterns and reservoirs levels variations, the authors proposed the use of a multi-objective genetic algorithm (MOGA) connected to EPANET for the hydraulic behaviour evaluation and to a module for water demand prediction using neural networks. The main objectives were the minimisation of operational costs and maximisation of benefits from energy generation. The study of Gonçalves and Ramos [69] showed possible payback periods from 5 to 8 years for the installation of PATs.

The work of Ramos et al. [122] offers a comparative study for pressure control by using a pressure reducing valve (PRV) and a PAT for simultaneous energy recovery. Similar to Gonçalves and Ramos [69], Ramos et al. [122] stated that, for PATs in the range of 5–500 kW, the payback time is significantly inferior than for a conventional turbine (less than 5 years). In their work, the authors developed a mathematical model linking EPANET to a GA for the minimisation of the nodal pressure by valve control subject to a constraint for the established minimum pressure. Performance curves of different pumps in the two operating modes (pump and turbine) were developed in order to select the best characteristic curve of the turbo-machine to be used to control pressure. The micro-hydro implementation was conducted in a case study at Algarve (Portugal), in a network beginning at the Beliche dam, passing through a pump station and continuing to the treatment plant. Results have shown similar operation conditions by either using a PAT or a PRV. However, installations with hydropower systems allow a considerable energy reduction by using its own generation [122].

A recent study dealing with quarter-hourly operation was published [159]. The model presented in this study handles hydropower reservoirs with pump storage plants. The optimisation problem was divided into seven sub-horizons of 6 h each and a quarter-hourly scheduling was performed. The authors believe that this procedure could be one of the keys to make this kind of problem easier to solve, avoiding, for example, the problem of the schedules providing simultaneous generating and pumping (identified in some 1-h time-step problems according to Wang and Liu [159]).

The work of Castronuovo and Lopes [21] deals with the operational optimisation of a network containing a hybrid wind-hydro power plant. The wind power forecast is obtained by time-series, for a time horizon of 48 h. The daily operation strategy for each one of the determined time-series scenario is optimised by a linear hourly-discretised algorithm. The predicted average economic gain of this optimisation was assumed to be between 425.3 and 716.9 k€ for an analysed test case. The authors also refer that the use of water storage ability allows improving the hybrid wind-hydro park profits. This is because the energy can be delivered to the network during the peak energy price [21].

Vieira and Ramos [151] presented a work dealing with hydro-turbines and wind power generation for pumping supply. A simplified system containing a pump station and excess of available energy in the gravity branch was tested. In order to use this excess energy, the existent pressure reducing valve was replaced by a water turbine. A model based on LP and linked to EPANET was used to optimise the pump station operations during 24 h of simulation, considering the reservoirs levels variations as the decision variables [151]. Operations for both winter and summer conditions were also considered. With the pumping operations optimisation, energy costs were saved up to 47%. Considering the inclusion of a wind turbine, the electricity needs for pumping the water were almost filled. The daily economic benefits obtained in the gravity system demonstrated to be dependent on the available energy, initial level of the downstream reservoir and its capacity [151].

Later, in Madeira (Portugal), the Socorridos WSS, a system with water consumption and inlet discharge, was tested with the methodology proposed by Vieira et al. [150]. The authors used Linear Programming and Nonlinear Programming tools for the operational optimisation and again used EPANET for the hydraulic simulation. Savings of nearly 100€/day were obtained with the Nonlinear Programming approach and, when a wind park is added to the system, the profits are approximately 5200€/day. The pump and turbine controls, using NLP with and without wind turbines, were different from each other due to the nonlinearity of the objective function and also due to the availability of wind energy [150].

5. Water industry requirements

Most developed methodologies for water systems improvement have been oriented towards determining least-cost design and pump-scheduling strategies. However, the acceptance of some innovative methods by water industries for real applications can be partially limited due to [123]: (a) the confinement of some techniques to minimise energy costs ignoring the network performance, (b) the complexity of the problem formulation due to considerable amount of mathematical sophistication, (c) the complexity of the networks that is dependent on their size, (d) usually oversimplification of the systems and (e) the excessive run times and easy trapping at local optima.

For a better acceptance of the methods by the industry, it is important to develop robust software programmes applying the corresponding methods with: (a) intuitive and attractive graphic interfaces, (b) easy adaptation to new situations and, maybe the most important issue, (c) paying specific attention to the network performance and the consumers supply requirements. For the guarantee of this last topic, the use of a calibrated hydraulic simulator in order to reflect the true operational characteristics of the networks is crucial. The calibration process requires a considerable amount of data, usually collected manually, and manipulation of model variables [95]. Bunn [16] also pointed out that any optimised solution must (i) be obtained quickly enough to respond to real-time changes in the system, (ii) not interfere with protection mechanisms and (iii) not cause negative impact on water quality.

The best way to reach all these objectives is by working in parallel with the water industries during the methodologies development in order to respond to particular industry requirements. At the same time it is important to notice that the best way to meet all the needs implies the use of a combination of complementary tools in order to manage the complexity of water-related challenges [103].

For the analysis of real water systems efficiency, global and local water situations should be assessed and then a focus on critical points should be done, implementing action and setting targets. During these steps, water risks must be identified and controlled through monitor and communication means. Even after completing all these, water companies should revisit their strategies and reassess opportunities for continuous improvement [103].

6. Discussion

Water Supply Systems are characterised by a large variety and complexity providing a huge opportunity to act in the economic and/or energetic efficiency improvement. For the distinct existing networks there are several possible measures to apply, where some of them imply large investment and others not so much.

Although the installation of Variable Speed Drives in pumps allied to the control optimisation may provide the greatest reductions of energy and costs associated to the network operation, it should be noticed that this measure is more capable of providing such results in installations presenting flow rate variation. For installations with no flow rate variation, the energy tariff can always be checked and maybe changed by a more suitable one.

Despite the high investment cost, the implementation of hydro-turbines in areas containing excessive pressures can be an attractive measure when presenting low payback times.

The use of hydraulic simulators is essential during the application of improvement measures in order to guarantee proper operation of the networks. The choice of the hydraulic simulator presents a significant impact on the optimisation process since it determines the feasibility of the optimal solutions. A quick evidence of this fact can be observed, for instance, when some solutions obtained in older studies are considered not feasible in current studies due to the use of improved hydraulic simulators. It is observed that studies making use of EPANET 2.0, for example, have resulted in better solutions (see resume of results in Appendix A1–A6). For this reason, it could be interesting to test some of the most popular hydraulic simulators to find which one provides the most approximate representation of the real behaviour of the systems.

For real applications, the use of calibrated hydraulic simulators is decisive for the success of the improvement measures. The process of calibrations of such models can usually represent the most time-consuming step in the entire optimisation process of a WSS.

Still concerning the optimisation, it is possible to identify the need of some studies comparing the performance of several algorithms in a network containing all possible complexities existent in the real world. In the case of the design optimisation, the use of benchmark networks for comparative studies has been very common. However, the same is not occurring for operational optimisation. Another important issue is related to the lack of comparative studies performed under the same conditions such as the constraints and initial parameters considered for the networks modelling.

A tendency of several researchers for applying GA in the WSSs optimisation can be explained by the great performance of this algorithm in several complex engineering problems. However, the investigation of other efficient and robust techniques remains open for future works.

Table A1
Resume of the distinct methods, available in the literature, applied for the design optimisation of the two-loop network.

Two-loop								
Authors	Year	Method	Hydraulic simulation	Best cost ($ M)	Evaluations number	Feasible solution? (according to)	Sources	Other observations
Alperovits & Shamir	1977	Decomposition	–	0.498	–	–	Alperovitz & Shamir, 1977	–
Gouler et al.	1986	Decomposition	–	0.435	–	–	Geem, 2009	–
Kessler & Shamir	1989	Decomposition (matrix notation)	–	0.418	–	–	Kessler & Shamir, 1989	–
Fujiwara & Khang	1990	–	–	0.415	–	–	Djebedjian et al., 2000	–
Eiger et al.	1994	Decomposition (Branch and Bound)	–	0.402	–	-	Eiger et al., 1994	–
Savic & Walters	1997	GA (GANET)	EPANET	0.419	25000	–	Savic & Walters, 1997	–
Abebe & Solomatine	1998	GLOBE	EPANET	0.419	1373	–	Abebe & Solomatine, 1998	–
Cunha & Sousa	1999	SA	–	0.419	70000	–	Djebedjian et al., 2000 Geem, 2009	w=10,5088
Djebedjian et al.	2000	SUMT	–	0.419	–	–	Djebedjian et al., 2000	–
Wu et al.	2001	GA	–	0.419	7467	–	Geem, 2009	w=10,5088
Eusuff & Lansey	2003	SFLA	EPANET	0.419	11155	–	Eusuff & Lansey	w=10,6668
Cunha & Ribeiro	2004	Tabu Search	–	0.42	–	–	Cunha & Ribeiro, 2004	–
Liong & Atiquzzaman	2004	SCE	EPANET	0.419	1091	–	Liong & Atiquzzaman, 2004	–
Geem	2006	HS	EPANET	0.419	1067	–	Geem, 2006	w=10,6668
Geem	2009	PSHS	EPANET 1.0	0.419	204	–	Geem, 2009	w=10,6668
Formiga et al.	2006	NSGA-II	Gradient method	0.450	5937	–	Formiga et al., 2006	use of D-W formula instead of H-W and leakages consideration

Table A2
Resume of the distinct methods, available in the literature, applied for the design optimisation of the two-reservoir network.

Two-reservoir								
Authors	Year	Method	Hydraulic simulation	Best cost ($ M)	Evaluations number	Feasible solution? (according to)	Sources	Other observations
Gessler	1985	Selective Enumeration	–	1833	–	–	Simpson et al., 1994	–
Simpson et al.	1994	Complete enumeration	–	1750	11940	–		–
		NLO (GINO)	Wadiso	1760	–	–		–
		GA	Newton-Raphson solver	1750	50000	–		–
Wu & Simpson	2001	messy GA	–	1750	2400	–	Wu & Simpson, 2001	–
Maier et al.	2003	ACO	Wadiso	1750	8509	–	Maier et al., 2003	–
Cheung et al.	2003	SPEA	EPANET 2.0	1667	–	–	Cheung et al., 2003	2 objectives: cost & pressure deficit minimisation
Zecchin et al.	2007	AS(elite)	EPANET 2.0	1750	1800	–	Zecchin et al., 2007	–
		AS(rank)		1750	1500	–		–

Table A3
Resume of the distinct methods, available in the literature, applied for the design optimisation of the Anytown network.

Anytown								
Authors	Year	Method	Hydraulic simulation	Best cost ($ M)	Evaluations number	Feasible solution? (according to)	Sources	Other observations
Gessler	1985	Enumeration	–	12.3	–	–	Walski et al., 1987	–
Lee et al.		Gradient search & LP	–	12.9	–	–		–
Morgan & Goulter		Hardy-Cross method & LP	–	13	–	–		–
Ormsbee		Box-Complex search	–	13.8	–	–		–
Murphy et al.	1994	–	–	11.4	–	–		–
Walters et al.	1999	SMGA (2 objectives: max benefit & min cost)	–	10.9 (cheapest)	–	–	Walters et al., 1999	pumping and storage included
			–	11 (preferred)	–	–		
Farmani et al.	2006	Evolutionary Multi-objective (max reliability, min cost & residence time)	EPANET 2.0	13.4 (cheapest)	–	–	Farmani et al., 2006	pump operation schedules included
Olsson et al.	2009	NSGA-II	–	20.6	–	–	Olsson et al., 2009	Multi-objective (results for zero deficits)
		UMDA		15.9				
		hBOA		17.9				
		CSM		16.1				

Table A4
Resume of the distinct methods, available in the literature, applied for the design optimisation of the New York City Tunnels network.

New York City Tunnels								
Authors	Year	Method	Hydraulic simulation	Best cost ($ M)	Evaluations number	Feasible solution? (according to)	Sources	Other observations
Schaake et al.	1969	LP & DP	–	78.09	–	Yes (Dandy et al., 1996)	Dandy et al., 1996 Geem, 2006	–
Quindry et al.	1981	–	–	63.58	–			–
Gessler	1982	–	–	41.8	–	Yes (Dandy et al., 1996) No (Savic & Walters, 1997)	Dandy et al., 1996; Savic & Walters, 1997	–
Bhave	1985	–	–	40.18	–			–
Morgan & Goulter	1985	–	–	39.2	–	No (Dandy et al., 1996)	Dandy et al., 1996	–
Kessler	1988	–	–	39	–			–
Fujiwara & Khang	1990	–	–	36.1	–			–
Murphy et al.	1993	–	–	38.8	–	No (Savic & Walters, 1997)	Savic & Walters, 1997	–
Dandy et al.	1996	improved GA	KYPIPE	38.8	96750	–	Dandy et al., 1996	–
Savic & Walters	1997	GA (GANET)	EPANET	37.13	1000000	No (Savic & Walters, 1997)	Savic & Walters, 1997	w=10.5088
				40.42	–	Yes (Savic & Walters, 1997), No (Zecchin et al., 2007)		w=10.9031
Lippai et al.	1999	Tabu Search	–	40.85	–	–	Geem, 2006	–
Wu & Simpson	2001	messy GA	EPANET	38.8	48387	–	Wu & Simpson, 2001	–
Cunha & Sousa	2001	SA	–	37.13	–	–	Geem, 2006	–
Wu & Simpson	2002	fast messy GA with self-adaptative boundary search	EPANET	38.8	30000	–	Wu & Simpson, 2010	–
Matías	2003	GA	–	38.64	–	–	Montalvo et al., 2008	–
Maier et al.	2003	ACO	Wadiso	38.64	13928	–	Maier et al., 2003	w=10.6668
Eusuff & Lansey	2003	SFLA	EPANET	38.13	–	–	Eusuff & Lansey, 2003	w=10.6668
Cunha & Ribeiro	2004	Tabu Search	–	37.1	–	No (Geem, 2009)	Cunha & Ribeiro, 2004	–
Geem	2006	HS	EPANET	36.66	6000	–	Geem, 2006	w=10.5088
Zecchin et al.	2007	AS(rank)	EPANET 2.0	38.64	19300	–	Zecchin et al., 2007	–
Montalvo et al.	2008	PSO	–	38.64	–	–	Montalvo et al., 2008	–
Perelman et al.	2008	Cross Entropy	–	38.64	–	–	Perelman et al., 2008	Multi-objective
Olsson et al.	2009	NSGA-II	–	38.64	–	–	Olsson et al., 2009	Multi-objective (results for zero deficits)
		UMDA	–	39.25	–	–		
		hBOA	–	44.56	–	–		
		CSM	–	46.40	–	–		
Geem	2009	PSHS	EPANET 1.0	38.64	4475	–	Geem, 2009	w=10.6668
Vasan & Simonovic	2010	DE (DENET)	EPANET 2.0	38.64	30701	–	Vasan & Simonovic, 2010	–
Bragalli et al.	2012	MINLP (Bonmin)	EPANET 2.0	36.38	–	–	Bragalli et al., 2012	w=10.5088

Table A5
Resume of the distinct methods, available in the literature, applied for the design optimisation of the Hanoi network.

Hanoi								
Authors	Year	Method	Hydraulic simulation	Best cost ($ M)	Evaluations number	Feasible solution? (according to)	Sources	Other observations
Fujiwara & Khang	1990	NLPG & local improvement	–	5.562 6.320	–	No (Eiger et al., 1994)	Eiger et al., 1994 Geem, 2006	–
Eiger et al.	1994	Decomposition (Branch and Bound)	–	6.027	–	No (Savic & Walters, 1997)	Eiger et al., 1994	–
Savic & Walters	1995	GA	–	6.195	–	–	Montalvo et al., 2008	–
Savic & Walters	1997	GA (GANET)	EPANET	6.073	1000000	–	Savic & Walters, 1997 Geem, 2006	–
Abebe & Solomatine	1998	GLOBE	EPANET	7.006	16910	–	Abebe & Solomatine, 1998	–
Cunha & Sousa	1999	SA	–	6.056	53000	No (Eusuff & Lansey, 2003)	Geem, 2006	–
Wu et al	2001	GA	–	6.182	–	–	Montalvo et al., 2008	–
Matías	2003	GA	–	6.093	–	–		–
Cunha & Ribeiro	2004	Tabu Search	–	6.056	–	–	Cunha & Ribeiro, 2004	–
Liong & Atiquzzman	2004	SCE	EPANET	6.220	25402	–	Liong & Atiquzzman, 2004	–
Geem	2006	HS	EPANET	6.056	200000	–	Geem, 2006	w=10.6668
Zecchin et al.	2007	MMAS	EPANET 2.0	6.134	85600	–	Zecchin et al., 2007	–
Montalvo et al.	2008	PSO	–	6.133	–	–	Montalvo et al., 2008	–
Geem	2009	PSHS	EPANET 1.0	6.081	17980	–	Geem, 2009	w=10.6668
Vasan & Simonovic	2010	DE (DENET)	EPANET 2.0	6.056	50201	–	Vasan & Simonovic, 2010	–
Bragalli et al.	2012	MINLP (Bonmin)	EPANET 2.0	6.056	–	–	Bragalli et al., 2012	–

One of the main question that is pointed out for the control optimisation problems is concerning the decision for the optimisation variables formulation. Should an explicit formulation be the best choice since it deals directly with pumps or perhaps an implicit formulation (such as the tanks water levels variation) could provide better solutions? When dealing with fixed-speed pumps and, at the same time, when tanks are directly connected to the pump stations, the relation between tanks water levels variations and the desired pump controls for such variations can be easy. However, in complex networks, the decision of the best pumps operation according to certain variations in water tanks levels can be difficult. It is the case when the networks present

Table A6
Resume of the results of the application of distinct optimisation methods for the control optimisation of different water supply systems.

Authors	Year	Optimisation method	Constraints (in case of violation…)	Objectives	Type of control	Tested networks	Results (cost reduction, number of iterations, CPU time)	Source	Other observations
Cembrano et al.	1988	Conjugate Gradient	state and boundary constraints (penalty functions)	single-objective (min cost)	pump and valve control (24h - 1h intervals)	Barcelona (Spain)	1.7 $M, _, 24 min	Cembrano et al., 1988	no continuity
Brion & Mays	1991	Generalised Reduced Gradient (KYPIPE)	(penalties trhough Augmented Lagrangian method)	single-objective (min cost)	pump control (24h - 2h intervals)	Austin (Texas)	191 $ (-17.3%)	Brion & Mays, 1991	_
Mackle et al.	1995	GA	tank levels and continuity (penalty functions)	single-objective (min cost)	pump control (24h - 1h intervals) on/off	source - 4 pumps - reservoir	_	Mackle et al., 1995	obtained an optimised pump schedule adapted to the energy tariff variation
Savic & Walters	1997	GA	tank levels and continuity (progressive penalties technique)	multi-objective (min: energy costs; max: pump switches and feasibility)	pump control (24h - 1h intervals) on/off	source - 4 pumps - reservoir	_	Savic & Walters, 1997	initial population based on previous runs improves the efficiency and the solutions
Goldman & Mays	1999	SA	tank levels, continuity, pressure bounds, water quality	single-objective (min cost)	pump control (24h- 2h intervals) on/off	Austin / North Marin (California)	$221.38 (-4.1%) / $429.53	Goldman & Mays, 1999	the model can be easily adapted to a SCADA system
Atkinson et al.	2000	GA	_	_	_	Richmond (UK)	38300£ (-19%), 150000, 69 hours	Van Zyl et al., 2004	use of a commercial hydraulic simulator very time consuming which affected the final results
Cembrano et al.	2000	Generalised Reduced Gradient (WATERNET)	_	single-objective (min cost)	valve and pump control on/off	Sintra (Portugal)	(-18%)	Cembrano et al., 2000	Real-time operations (SCADA)
Pegg	2001	Decerto	_	single-objective (min cost)	half-hour control of fixed-, variable- and dual-speed pumps	Wainuiomata-Waterloo network (Wellington)	(-10%)	Pegg, 2001	Real-time operations (Citect SCADA system)
Barnett et al.	2004	WaterGEMS	_	single-objective (min cost)	pump and valve control on/off	Jacksonville (Florida, USA)	_	Barnett et al., 2004	Real-time operations (SCADA)
Van Zyl et al.	2004	Pure GA	tank levels and number of pump switches	single-objective (min cost)	pump control on/off	case study / Richmond (UK)	350.36£, 100000 / 35296£ (-26%), 200000	Van Zyl et al., 2004	better performance of the hybrid using Hooke and Jeeves method than the Fibonacci
		Hybrid GA + Hill Climber (Fibonacci / Hooke&Jeeves) + EPANET					348.58£, 6000 / <35500£, 8000		
Carrijo et al.	2004	elitism-based SPEA (Strenght Pareto Evolutionary Algorithm) + EPANET2	_	multi-objective (min costs; max hydraulic benefits - index for pressure, demands and reservoir levels)	pump and valve control (24h - 1h intervals) on/off	Goiânia (Brazil)	good performance on finding the pareto-front	Carrijo et al., 2004	_
Lücken et al.	2004	Sequential and parallel implementation of: MOGA, NPGA, NSGA, SPEA, NSGA-II and CNSGA-II	_	multi-objective (min: energy cost, number of pump switches, power peak and reservoir level variation)	Pump control on/off	source - pump station (5pumps) - reservoir	several improvements of parallel over sequential MOEAs	Lücken et al., 2004	_
López-Ibáñez et al.	2005	SPEA2 + EPANET	tank levels and nodal pressures (constraint handling method based on ranking solutions)	multi-objective (min energy costs and number of pump switches)	pump control (24h - 1h intervals) on/off	Van Zyl	solutions that dominate the solution obtained by the correspondent algorithm in a single-optimisation approach	López-Ibáñez et al., 2005	_
Firmino et al.	2006	LP & ILP	continuity, max pump flow, reservoir levels	single-objective (min cost)	pump control on/off	Campina Grande (Brazil)	(-15%)	Firmino et al., 2006	_
Bunn	2007	Aquadapt	_	move energy use, reduce peaks and energy required by pumps	_	EBMUD / Washington	(-13.1%) / $1000	Bunn, 2007	Real-time operations
Salomons et al.	2007	DRAGA-ANN	pressure, tank levels, maximum pump power consumption and velocity	single-objective (min cost)	pump control (24h - 1h intervals) on/off	Haifa-A (Mount Carmel)	(-25%), _, faster than GA-EPANET	Salomons et al., 2007	Real-time operations (SCADA)
Martínez et al.	2007					Valencia (Spain)	(-17.6%)	Martínez et al., 2007	
López-Ibáñez et al.	2008	parallel ACO + EPANET	_	reduce CPU time	_	Richmond (UK)	_, 8000, <0.5h (around 2h with sequential ACO)	López-Ibáñez et al., 2008	in the parallel ACO, a higher number of ants reduces CPU time
Wang et al.	2009	GA	reservoir levels & flow in the system, to avoid underflow or overflow (penalty functions)	multi-objective (min cost, number of pump switches and total work time for each pump)	pump control on/off	source - pump station (several pumps) - reservoir	convergence speed could be improved	Wang et al., 2009	first work considering the land subsidence due to groundwater pumping all day long
Shihu et al.	2010	hybrid GSA (Genetic Simulated Annealing) + EPANET	tanks water levels, continuity, velocity limit of variable-speed pumps, number of switches	single-objective(min total cost = water production costs + electricity costs)	fixed- and variable-speed pumps control	City T (China)	(-6%)	Shihu et al., 2010	_
Bene & Hos	2011	MINLP, SBB / Series of Local Optima Technique, SLO	_	single-objective (min cost)	least-cost filling reservoir with a variable-speed pump without time constraints	source - pump - pipes - upper reservoir - consumption	SLO gives pump schedules with lower energy consumption (12.65 $) - better results for smaller time steps	Bene & Hos, 2011	decision variables - reservoir levels
López-Ibáñez et al.	2011	Simple Evolutionary Algorithm, SEA + EPANET	tank levels, continuity, pressure head, number of pump switches, EPANET warnings (constraint handling method based on ranking solutions)	single-objective (min cost)	pump control (24h - 1h intervals) on/off	Van Zyl /Richmond (UK)	315.9£ / _	López-Ibáñez et al., 2011	SEA with time-controlled triggers demonstrated better performance when compared to SEA with both binary and level-controlled triggers
Mouatasim et al.	2012	SPRG	population supply guarantee; tank levels	single-objective (min cost)	pump control on/off	Kénitra City /Agadir City (Morocco)	winter - 344.7$ / 937.44$ summer - 61.83$ / 278.37$	Mouatasim et al., 2012	_
		LINGO					winter - 516.3$ / 1001.25$ summer - 68.67$ / 278.37		

variable-speed pumps, several pumps with distinct characteristics, multiple storage tanks with no direct connexion to the pump stations, etc. In such cases, the explicit optimisation of pumps (and even valves) may allow achieving better solutions. On the other hand, dynamic optimisation could be an option to solve these more complex cases through an implicit formulation.

Regarding the influence of the connexion between real-time systems and optimisation modules, it is worth noticing that no investigations were made in the ability of the algorithms to adapt to small changes in constraints conditions such as on-line changes in predicted demand and current reservoir levels.

By analysing the collected works related to water demand prediction, the advantage of combine distinct forecast models becomes clear. Artificial Neural Networks, for example, can present a great performance when enough historical data is available for the process of training required by this method. However, when these kinds of methods fail, time-series and regression models can provide some guarantees. It is most important to refer that the stage of water prediction during an optimisation process determines the success of reaching the best solution.

Scientific works, as the ones presented in this manuscript, developed in parallel with water companies will present higher probability of success and feasibility in the large variety of real systems since they allow important adaptations during the development and the implementation of innovative techniques and methodologies. Furthermore, as it became clear in this discussion section, both the reviewed subjects present decisive contributions for the achievement of the best efficiency improvements and, for this reason, should not be treated separately. The process of optimisation of a water network, for example, can never provide significant improvements (i) if the hydraulic model for simulation is not adequate, (ii) if the water demand prediction model fails, or even (iv) if the formulation of the problem being solved does not consider specific requirements of the system.

7. Conclusion and final remarks

This review paper explores a number of measures and, mostly, provides state-of-the-art optimisation techniques focused on the design and operation of WSSs. Water quality and sewer water are topics not discussed in this work. However, the authors do not set aside the importance of these issues for the global improvement of a WSS. For example, the energy recovery from sewage sludge can present a huge opportunity for improving the efficiency of WSSs.

Since the attention to the sustainability in the world is continuously growing, the importance of including hydro, wind and/or solar energy systems in this field is also increasing. This inclusion not only contributes towards the sustainability of the water systems but also promotes the development of clean and renewable energy production, reducing the dependence of fossil fuels and consequently reducing environmental impact. However, as already referred by Ramos et al. [122], some energy policies required to impose the implementation of these strategies by water companies are missing.

The concept of smart water networks (or smart grids for water) is an emerging market similar and parallel to the established electrical smart grids. According to the IDC Energy Insights report "Smart Water Market Overview" (see [136]), smart water network management solutions will grow faster than smart water metering and the major benefits will correspond to water loss reduction. The solutions presented in this review paper, especially the ones related to the networks automation and real-time operation, can reveal a huge contribution for the development of this recent concept.

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Appendix A

See Tables A1–A6 here.

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